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Adaptive Integration and Optimization of Automated and Neural Processing Systems—Establishing Neural and Behavioral Benchmarks of Optimized Performance

by Laurie Gibson, Jon Touryan, Anthony Ries, Kaleb McDowell, Hubert Cecotti, and Barry Giesbrecht

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Adaptive Integration and Optimization of Automated and Neural Processing Systems—Establishing Neural and Behavioral Benchmarks of Optimized Performance

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14. ABSTRACT

Technical advances intended to improve situational awareness by providing more information about the tactical environment place high demands on the Soldier's limited-capacity cognitive and neural systems. Information display technologies have been developed that filter information to prevent performance failures due to information overload. However, these technologies are typically rigid with respect to changes in the operator's physical and cognitive state. Thus, a further objective of the project described in this report is to develop an adaptive framework that adjusts filtering algorithms to optimize human performance in a variety of operational contexts. The work adopts a unique approach that integrates measures of behavior, brain activity, and physiology with automated information processing and display algorithms. It leverages basic science research conducted at the Institute for Collaborative Biotechnologies (ICB) that uses machine learning algorithms to detect performance failures during difficult attentional tasks based on brain activity, work done at Science Applications International Corporation (SAIC) using pattern classification algorithms to detect threats based on brain activity, and work done at the U.S. Army Research Laboratory/Human Research and Engineering Directorate (ARL/HRED) that is aimed at understanding the cognitive constraints on performance in crew stations.

15. SUBJECT TERMS

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Executive Summary

The future force design of manned ground vehicles (MGV) will place increasing workload demands on smaller crews and require a high operational tempo. A significant component of the Soldier's workload will be to maintain situational awareness of the vehicle surroundings using indirect vision. While the indirect vision systems are supposed to facilitate increased situational awareness, the increase in the amount of information may exceed the crew's cognitive capacity. This project aims to enhance Soldier performance within this context by combining neural and physiological measures of perceptual and attentional state to dynamically adapt the presentation of information to optimize sustained surveillance of the vehicle perimeter with only minimal cognitive workload. The goal is to allow the Soldier to attend to relevant battlefield objects of interest using new technologies at the critical interface between the Soldier and the system.

Technical advances intended to improve situational awareness by providing more information about the tactical environment place high demands on the Soldier's limited-capacity cognitive and neural systems. Information display technologies have been developed that filter information to prevent performance failures due to information overload. However, these technologies are typically rigid with respect to changes in the operator's physical and cognitive state. Thus, a further objective of the project described in this report is to develop an adaptive framework that adjusts filtering algorithms to optimize human performance in a variety of operational contexts. The work adopts a unique approach that integrates measures of behavior, brain activity, and physiology with automated information processing and display algorithms. It leverages basic science research conducted at the Institute for Collaborative Biotechnologies (ICB) that uses machine learning algorithms to detect performance failures during difficult attentional tasks based on brain activity, work done at Science Applications International Corporation (SAIC) using pattern classification algorithms to detect threats based on brain activity, and work done at the U.S. Army Research Laboratory/Human Research and Engineering Directorate (ARL/HRED) that is aimed at understanding the cognitive constraints on performance in crew stations. This project will be conducted over three years. In Year 1, which has been completed, benchmarks and key display parameters were determined for the performance of attentionally demanding tasks. During Year 2, the parameters established in the first year will be instantiated in more realistic situations and scenarios. Finally, the work in Year 3 will emphasize the optimization of the entire system to improve operator performance. This project reflects an integrated partnership that capitalizes on the strengths of the ICB, SAIC, and ARL/HRED co-investigators. Critically, this work has already helped support High-Definition Cognition in Operational Environments (HD-Cog) Army Technology Objective (ATO) technologies. Moreover, this work will enhance the work in Brain-computer Interactive Technologies (BCIT) in the Translational Neuroscience Branch in ARL/HRED.

This report describes the results of 10 separate studies that were conducted by the team in the first year.

1. Introduction

With advances in display and sensor technologies and with increased emphasis on a smaller, more mobile fighting force, today's Soldier must deal with a density and complexity of information that was unknown in the past. Although the intent of providing Soldiers with more information is to improve their situational awareness and operational performance in tactical situations, the increased informational content places high demands on limited capacity cognitive and neural systems. Various automated filtering algorithms and adaptive displays have been developed to help reduce the amount of information presented to the Soldier, but these algorithms are rigid and do not adjust based on the user's cognitive capacity, strategies, and level of stress. As a result, their inefficacy can result in suboptimal use. Ultimately, even with high performance automated filtering systems, the burden is on the Soldier to act on the information in dynamic, complex environments. Therefore, it is critical to develop technologies that will allow the integrated human-machine system to be highly adaptive to any context.

This report documents the results of the first year's work on a 3-year project to develop an approach for the integration of measures of neural activity into complex multi-platform human-machine systems that will provide real-time classification of cognitive and perceptual states and dynamic, adaptive adjustment of information displays to accommodate fluctuations in these states. The project builds upon key basic research conducted at the Institute for Collaborative Biotechnologies (ICB) applying measures of brain activity to classify performance failures during difficult attentional tasks. The aim of the first year of the 3-year project was to establish the fundamental parameters for optimizing attentional state classification in dynamic tasks from measures of brain activity. These measures will be integrated with other measures of behavioral performance and physiology and instantiated in hardware and software to monitor and optimize Soldier performance the parameters. This work has already provided benefit to High-Definition Cognition in Operational Environments (HD-Cog) Army Technology Objective (ATO) due to its emphasis on an integrated framework that takes into account both the automated systems that Soldiers use, as well as measures of performance, neural activity, and physiology. Additionally this work will help support Brain-computer Interactive Technologies (BCIT) within the Translational Neuroscience Branch of U.S. Army Research Laboratory/Human Research and Engineering Directorate (ARL/HRED).

The work during Year 1 had four research objectives supported by 10 separate research studies. These objectives include:

1. Establish the basic parameters that optimize performance of a system using Rapid Serial Visual Presentation (RSVP) to display images for an operator. Consider both behavioral performance (the ability of the operator to detect and report target threats) and the

performance of an automated algorithm that classifies the images from the neural response of the operator.

2. Examine performance when RSVP is carried out in conjunction with a second task.
3. Develop methods for classifying attentional impairments from neural data.
4. Build and test an application (based on the SAIC real-time neural processing system) for displaying images and capturing an operator's neural and behavioral responses at the ARL/HRED facility.

This report begins with a discussion of the background for the technical approach. It then describes the tasks and deliverables and follows with a summary of the work. Finally, it covers each of the 10 studies and ends with a summary of the year's results.

2. Technical Approach

This 6.2 research project will transition basic research previously carried out by the ICB teammates on the classification of human performance failures during difficult tasks based on measures of brain activity. Within the past decade, pattern classification algorithms, or neural decoding techniques, have been applied to spatial patterns of activity measured with functional magnetic resonance imaging (fMRI) to classify the types of objects presented to and the perceptual states of observers (Haynes and Rees, 2005; Kamitani and Tong, 2005). While these neural decoding techniques applied to fMRI data provide important clues about the neuronal representation of information, application of fMRI measurements within a real-time field context is currently not feasible. The basic research conducted by ICB co-investigators Giesbrecht and Eckstein applies these classification techniques to high temporal resolution patterns of neural activity acquired with electroencephalography (EEG). While there are several reports of stimulus classification based on EEG measurements in the literature (Philiastides and Sajda, 2006a; Luo and Sajda, 2009), Giesbrecht and Eckstein have performed successful stimulus classification under difficult dual-task situations that are potentially relevant to the battlefield context (Giesbrecht et al., 2009; Ristic et al., 2009). In this dual-task paradigm, two visual targets (each backward masked by a pattern) are presented in rapid succession (see figure 1a). The first task (T1) required the discrimination of the direction of a central arrow that was flanked by arrows pointing in the same direction (easy) or in a different direction (hard). The second task (T2) involved discriminating whether T2 was related or unrelated to a context word presented at the very beginning of the trial. Typically in this dual task paradigm, correct identification of the first (T1) leads to impaired identification of the second (T2); a phenomenon known as the 'attentional blink' (Attentional Blink [AB], figure 1b).

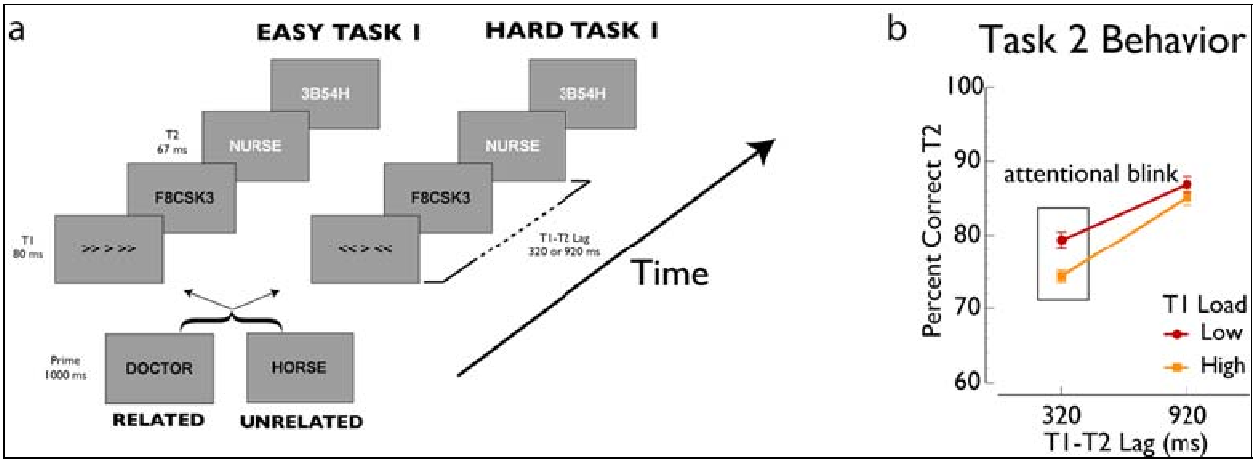

Figure 1. Dual-task paradigm and behavioral results. Panel a: Sample stimulus sequence. Each trial began with the presentation of a context word (1000 ms), followed by the presentation of the first target stimulus (80 ms), a visual mask, and the second target word (67 ms), and a visual mask. The temporal lag between the two targets (T1-T2 Lag) was either 320 or 920 ms. The first target task was to indicate the direction of the central arrow that was flanked by arrows pointing in the same direction (easy/low task load) or different directions (hard/high task load). The second target task was to indicate whether the target word was related or unrelated to the context word. Panel b: Behavioral performance on the second target task averaged across the sample (12 participants).

We applied a linear pattern classifier (i.e., linear discriminant analysis) to EEG data evoked by the T2 and evaluated performance of the classifier for separate post-T2 time points using a k-fold cross-validation scheme. Target amplitude was the primary classification feature. This analysis revealed several key findings. First, when the classifier was trained and tested on activity evoked by the second target, accuracy was above chance when the two targets were separated by enough time to be outside the typical AB time window (figure 2). This was true regardless of the difficulty (load) of the first target task. Second, during the typical AB time window when behavioral performance on the second target task is most impaired, the classifier was accurate only when T1-task load was low. Because the AB represents a failure of attention, these results indicate that patterns of neural activity recorded during periods when attentional capacity is pushed to its limits can be used to discriminate the information presented to the observer independent of behavior.

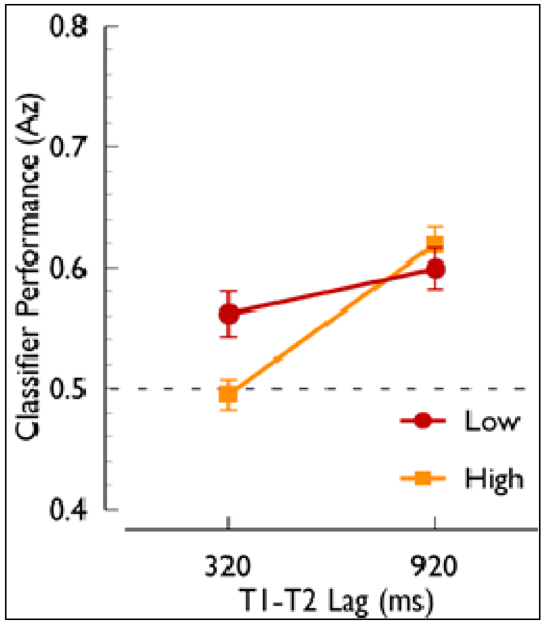

Figure 2. Performance of the classifier in discriminating whether the T2 word was related or unrelated to the context word. Classifier performance was quantified using a nonparametric measure of the area under the Receiver Operator Curve (Az). Separate classifiers were trained and tested on T2-evoked neural activity for each participant measured at central and parietal midline electrodes (Cz and Pz).

Another unique aspect of the ICB basic research, and perhaps the most critical one for the present work, is that various metrics obtained from the temporal patterns of EEG activity can be used to predict the observers' performance (Eckstein et al., 2008; Das et al., 2009; Giesbrecht et al., 2009). For instance, in the dual task paradigm described above, the classifier could accurately discriminate when the observers made an error during the AB based not only on activity evoked by the second target, but also by activity evoked by the first target (figure 3). In other words, the classifier could discriminate a performance failure on the second target before the second target was presented to the observer. Interestingly, the accuracy of classification errors was not constrained by task load.

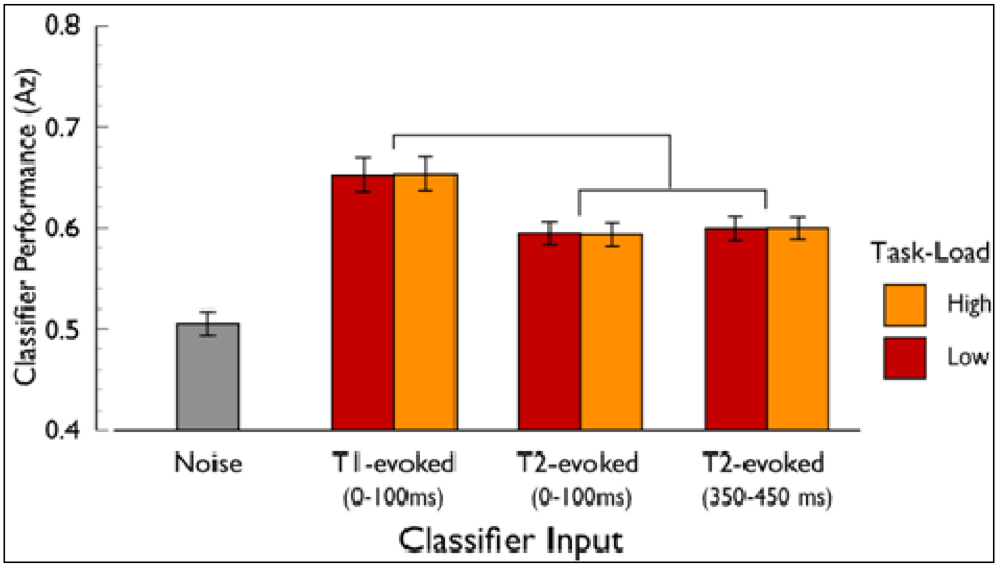

Figure 3. Classifier accuracy in discriminating attentional failures based on inputs derived from activity evoked during two periods after the second target, activity evoked the first target, and a Gaussian noise control.

The results of this ICB research suggest that pattern classification algorithms may be used to assess the attentional state of the Soldier on a moment-by-moment basis, thereby permitting performance to be optimized. Using classification algorithms to detect variations in attentional performance is the key technical solution that will be transitioned in the current 6.2 project. The application of classification algorithms to EEG is an important step towards real-time monitoring of the environment and crew station operator's perceptual and cognitive states and it is a natural point of collaboration between ICB faculty and current work being done by SAIC in more complex military contexts, and the ARL-led BCITs.

2.1 SAIC Applied and Transitional Research

In contrast to the basic research developed at ICB, SAIC's applied research and neurotechnology is based on established scientific observations describing how the human visual system processes and classifies complex imagery. For over a decade it has been known that the visual cortex can perform complex categorization of visual stimuli within a few hundred milliseconds of the stimulus presentation (Thorpe et al., 1996). In the original laboratory experiment, subjects were asked to determine if a photograph, presented for only a few milliseconds, contained an animal. Using EEG, researchers were able detect an animal/no-animal categorization signal emanating from the frontal and parietal cortex far earlier (150 ms) than any behavioral response could be initiated. Since the initial finding, various groups have expanded this work by having subjects perform more complex categorizations (Tanaka and Curran, 2001; Tanaka et al., 2005; Scott et al., 2008). This idea has also been extended to incorporate sequentially presented stimuli, known as the RSVP paradigm, for both still and motion imagery (Luo and Sajda, 2009).

SAIC's recent work has focused on transitioning this laboratory-based EEG research into a more applied context. Scientific studies that classify the perceptual state, based on EEG signals, require only statistical significance to demonstrate their validity. However, if this technology is to be utilized in an application, a much higher level of performance is required. Under the Defense Advanced Research Project Agency's (DARPA)'s Neurotechnology for Intelligence Analysts (NIA) program, SAIC developed EEG classification technology whose performance far exceeded any previously published result. In this project, Imagery Analysts (IAs) were asked to identify targets of military significance in satellite imagery (Curran et al., 2009). Using EEG classification, the SAIC algorithm was able to determine when the IA had seen a target only 120 ms after the image was presented. The classification accuracy exceeded 0.95 area under the Receiver Operating Characteristic (ROC) curve for many subjects.

Laboratory studies that utilize EEG to measure and classify perceptual states often use repeated trials to improve the signal-to-noise ratio and subsequent results. The underlying neural signatures associated with a perceptual state can often be clearly shown by averaging over repeated trials. However, for many applications of this technology it is critical to minimize the number of required stimulus presentations and to rapidly process the EEG signals. Again, under a DARPA program (Cognitive Technology Threat Warning System–[CT2WS]), SAIC developed a real-time system that processes the perceptual state of the subject on a trial by trial basis. Here subjects were asked to detect potential threats (vehicles, people, etc.) over a wide field-of-view. Regions with potential threats (determined by an automated detection algorithm) were presented to the subject as a sequence of short video clips (figure 4). Using only the subject's EEG signals, the real-time system identified which regions contained a potential threat. Each video clip was 500 ms long and was embedded in a sequence containing hundreds of such clips. Thus, subjects were able to screen thousands of clips in a matter of minutes, with EEG classification performance remaining high (figure 4). This real-time system was tested with live video from a high resolution imager in an operational environment at Yuma Proving Grounds in February, 2009.

The CT2WS real-time system, shown in figure 5, demonstrated the feasibility of implementing EEG classification technology in operational environments. First, it overcame some of the technical challenges inherent in acquiring and processing EEG. Using automated artifact detection algorithms, the real-time system could dynamically redisplay stimuli that were presented during periods of degraded neural signal which occur with subject movement or eye blinks. Second, it achieved a high level of performance in a stressful operational environment with live targets (i.e., live video feed) and distracting (i.e., crowded and noisy) surroundings.

The field test revealed a critical need to integrate the detection of more subtle attentional states into these systems. During the field test, subjects were required to switch between passively viewing the RSVP sequence on one screen and actively identifying targets, via a button press, on another screen. Often, during demanding portions of the test, classification performance would degrade. We hypothesized that the decreased performance was due to the attentional demands of task switching (Rogers and Monsell, 1995; Slagter et al., 2006). Our system, however, only classified the perceptual state of the subject without accounting for attentional focus or attentional load. Any future application of this system in a complex task environment, such as an MGV crew station, would be greatly enhanced by attentional measures. By incorporating the ICB research, a system for processing large amounts of imagery can be integrated into the type of multi-tasking environment found in MGVs.

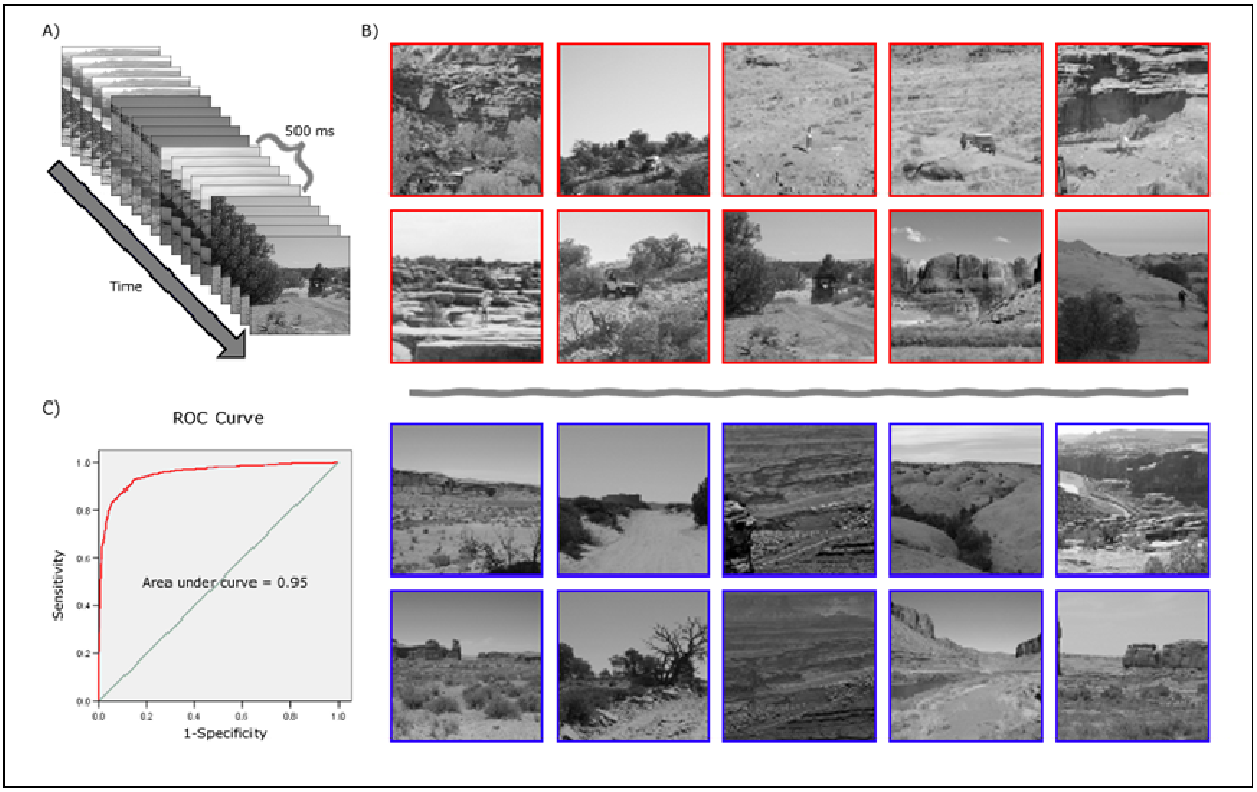

Figure 4. CT2WS paradigm and results. Panel a: Stimuli consisted of an RSVP sequence containing short (500 ms) video clips of potential targets and background clutter. Panel b: Video clips ranked by the neural response with colored border indicating ground-truth (red = target, blue = clutter); only the 10 highest and lowest scoring clips are shown. Panel c: Classifier performance for one subject quantified in an ROC curve (area under curve = 0.95). Note: imagery from the CT2WS program has not yet been approved for public release; images above are representative of stimuli used in the program.

Figure 5. The SAIC real-rime EEG Processing and Classification System in use in the laboratory (left) and in the field (right)

2.2 Approach to Research and Transition

Over a 3-year period, the current project will transition the ICB and SAIC work from basic science and proof of concept (6.1) into applied research (6.2) that will be applicable not only in the context of future force MGV concepts, but within any operational context that requires the Soldier to deal with multiple complex tasks and a number of display and sensor inputs. The effort will integrate the ICB finding that classification techniques can be used to assess attentional state with RSVP presentation and real-time EEG classification techniques previously developed by SAIC.

The key technical solution motivating the current project is the application of pattern classification algorithms to neural and physiological data to determine an observer's likelihood of making an attentional performance failure. The ICB basic research serves as the foundation which will be incorporated in SAIC's real-time, adaptive, automated neural processing system, and finally instantiated on Tank Automotive Research Development and Engineering Command (TARDEC) compatible platforms. The feasibility of this solution will be shown by addressing three fundamental scientific issues.

1. *Optimizing behavioral performance in the multi-task setting*. The demonstration of dual and multi-task performance impairments are ubiquitous in the scientific literature (Raymond et al., 1992; Pashler, 1994; Giesbrecht and Di Lollo, 1998; Giesbrecht et al., 2007). The key question here is whether there are methods of presenting critical information for multiple tasks that will minimize these impairments so as to optimize Soldier-system performance.

2. *Optimizing the classification of target threats based on neural data acquired in a multi-task setting*. In the case that operator performance cannot be optimized, the question is whether there are methods of presenting critical information for multiple tasks to ensure high neural decoding performance even though operator performance may fail. There is clear evidence

based on the work done at ICB, SAIC, and other laboratories that specific fluctuations in voltage measured by EEG, both those that are tied to sensory processing and those that are associated with later decisions and conscious perception, can be used to classify the stimulus presented to an observer (Philiastides and Sajda, 2006a, 2006b; Eckstein et al., 2008; Das et al., 2009; Giesbrecht et al., 2009). However, it is unclear how these signals (and consequently the efficacy of these neural decoding techniques) are affected by sensory, cognitive, and task conditions.

3. *Optimizing the classification of attentional impairments based on neural data*. Based on recent work done at ICB, there is the indication that neural decoding techniques may be effective in using attentional indices in predicting performance failures. It is an unresolved question as to what task and stimulus constraints along with what properties of the EEG signal (amplitude, phase, power, etc.) are most predictive of performance failures and how the detection of these failures is affected by task demands. Determining these constraints is critical for assessment of the feasibility of the technical solution.

3. Year One Tasks and Deliverables

During the first year of the project, the team performed the following tasks and met Milestones 1.1 through 1.3. Milestone 1.4 will be met with the delivery of this report.

3.1 Tasks

1.1 (ICB/SAIC) Conduct experiments to establish the basic parameter set for the RSVP task that optimizes performance in terms of metrics such as probability of detection and false alarm rate or the area under the ROC curve. Analyze the neurophysiological data collected during the experiments for features which allow categorization of attentional state.

1.2 (SAIC) Incorporate results from previous ICB 6.1 work into the SAIC real-time EEG processing application to include attentional measures.

1.3 (ARL) Integrate the basic SAIC real-time EEG processing application with the task generation hardware and software. Use the SAIC application as a guide for implementation with ARL EEG hardware.

1.4 (ICB) Define and implement a primary task to be carried out with the secondary scanning/RSVP task so that subject performance can be measured and task complexity can be manipulated.

1.5 (ARL) Incorporate the results of ICB/SAIC research (Task 1.1) in EEG processing module of the task generation hardware and software in order to optimize performance metrics such as probability of detection, state classification, and neural pattern categorization.

1.6 (ICB) Conduct experiments to develop parameters and guidelines for dual task applications.

1.7 (SAIC) Incorporate the results of Task 1.1 in the SAIC real-time application.

1.8 (SAIC) Integrate the SAIC real-time application with the primary task. Establish guidelines for the dual task implementation.

1.9 (SAIC/ARL) Define a set of performance metrics that can be used throughout the project to assess improvements to the application. These metrics should be relevant to the application of RSVP in a dual task paradigm and support meaningful comparisons with standard methods of performing these tasks. SAIC will conduct tests on the real-time EEG dual task application and collect baseline performance metrics.

3.2 Technical Deliverables (Quarterly Milestones)

1.1 (SAIC) Algorithms, software, and documentation, which specify hardware requirements, constraints, and design guidelines for the incorporation of the basic SAIC real-time EEG processing in transitional hardware at ARL.

1.2 (ICB) Report documenting the experimental results with performance tradeoffs and guidelines for the RSVP task parameters shown in table 1.

1.3 (SAIC) Algorithms, software, and documentation that incorporate the results of Task 1.1.

1.4 (ICB/SAIC/ARL) Year 1 final report documenting:

1.4.1 Experimental results, parameters, and guidelines for the basic RSVP task implementation in a real-time system and for implementation in dual task applications, including algorithms and software.

1.4.2 Performance metrics and test results for the SAIC real-time system.

1.4.3 Hardware and software guidelines for the integration of EEG processing with Army systems.

4. Year 1 Overview

The Year 1 work had four objectives:

1. Establish the basic parameters that optimize performance of a system using RSVP to display images for an operator. Consider both behavioral performance (the ability of the operator to detect and report target threats) and the performance of an automated algorithm that classifies the images from the neural response of the operator.
2. Examine performance when RSVP is carried out in conjunction with a second task.
3. Develop methods for classifying attentional impairments from neural data.
4. Build and test an application (based on the SAIC real-time neural processing system) for displaying images and capturing an operator's neural and behavioral responses at the ARL/HRED facility.

In order to meet these objectives, the team worked to build a collaborative environment in which each member contributed to the whole. In support of this goal, the group held quarterly meetings to discuss progress and exchange ideas. A share site was established to facilitate the exchange of data, imagery, and documents. From the beginning of the project, biweekly teleconferences were held to discuss the work of each group during the two week period. In the first quarter of the project, the team emphasized the convergence of the various experimental paradigms and methods of the three groups so that each group's results could be related within a common context. Because of this collaborative approach, the Year 1 (FY10) milestones were met, with each group performing different but complementary tasks.

The first year results are summarized by objective.

4.1 Objective 1: Optimize Performance with RSVP

Work on this objective focused on the parameters set out in table 1.

Under Task 1.1 of the SOW, the ICB and SAIC systematically examined the RSVP parameters from the proposal. The ICB conducted a series of studies that addressed RSVP rate and location in the visual field and target salience. These studies show that performance on a target recognition task degrades when the RSVP imagery is shifted away from a fixation point (the center of the visual field) and that the magnitude of the performance degradation increases at higher presentation rates.

SAIC has a large collection of EEG and behavioral data that was acquired in the laboratory and in field tests during the DARPA CT2WS project. Using this data, SAIC focused on analyses of parameters that affect classification performance in the real-time system, guided by results from

Barry Giesbrecht's previous (6.1) research. One critical parameter was identified in this analysis: target probability. This was particularly interesting because it explained in part why the SAIC real-time system behaved differently in the field than in the lab, something that hadn't been previously understood. This is an important finding for the overall project. In real world systems, targets often appear in groups which means a system must gracefully handle long periods when no targets are present interspersed with periods of very high target abundance.

Table 1. Experimental variables examined in Year 1 together with a summary of the results to date.

Variable	Example Conditions	Purpose	Results
RSVP location	1. Foveal 2. Peripheral	If performance is not impaired by a peripheral stream, then that might permit the operator to continue with primary risk.	Initial results show rapid fall off in performance as presentation shifts away from fixation.
Presentation Rate	1. Slow (3 Hz) 2. Fast (10 Hz)	If performance is unimpaired at high rates, this could potentially increase throughput.	Q1 study examined 8.5−12.5 Hz and found performance degrades at faster speeds.
Target Frequency	1. Low frequency (1:100) 2. High frequency (1:10)	Target frequency may alter observer performance, but perhaps not classifier performance.	This was identified as a key parameter. Performance degrades with very high target frequency.
Target Salience	1. Low 2. High	This will determine visibility constraints on observer and classifier performance.	Performance is limited by the observer's ability to see the target.
Target Size	1. Small (1° of visual angle) 2. Large 5° of visual angle.	This will determine minimum size constraints for peripheral presentation.	Performance is limited by the observer's ability to see the target.

Based on these observations from the CT2WS data, the ICB team designed and carried out a study to systematically examine the effects of target probability. The ICB team showed that the optimal range of target frequency is from 10−25%. When targets appear more frequently, both behavioral performance (the ability of the subjects to press a key when they see a target) and the performance of the neural signal classifier degrade. This confirmed SAIC's CT2WS analysis. Further evaluation by SAIC showed that the effect could be mitigated, to some degree, in a real-time system by an adaptive thresholding technique.

4.2 Objective 2: Understanding Dual-Task Performance with RSVP

One of the key undertakings for this year was to define and implement a dual-task paradigm that mimics the multi-tasking environment which is common in operational settings. In the original proposal, a specific primary task to control autonomous mobility was defined to be used with RSVP as a secondary task. The decision was made instead to define an auditory task that mimics an operator monitoring communications while simultaneously viewing images with RSVP. There were several compelling reasons for this change. Initial results by the ICB showed significant degradation in performance when the RSVP stream is presented away from fixation (even para-foveally). This means that if the primary task is also visual, the operator cannot easily perform both tasks simultaneously. In order to handle both tasks, the primary task must be interrupted periodically to present the RSVP sequence. In this type of implementation, the tasks are executed serially, without making significant, simultaneous demands on the cognitive resources of the operator. Since the goal of the Year 1 work was to examine the impact of RSVP on a task with shared cognitive resources, the team decided to implement a non-visual primary task.

The ICB conducted the initial cross-modal, dual-task study in the first quarter. For the particular auditory and visual tasks they used, they found that overall performance was impaired, particularly when the temporal interval between the two tasks was brief. During the second quarter, the ICB and SAIC teams worked together to define and implement a new set of auditory and visual tasks based on the SAIC real-time system. Both teams began running subjects in dual-task experiments. The ICB team found that there was no degradation in either behavioral or classifier performance when subjects were looking for visual targets either as a single task or while simultaneously listening for a target word. SAIC had similar results with a slightly more difficult cross-modal paradigm. SAIC also found that there is interference between the auditory and visual tasks in the form of delayed response times for the visual task when auditory stimuli are also present.

New results uncovered in this research are that RSVP can be used in conjunction with common auditory tasks, such as monitoring communications. The results also point to the possibility of building a second classifier for auditory target recognition that can be operating in parallel with the RSVP classifier in a real-time system.

4.3 Objective 3: Classifying Attentional Impairments

By the third quarter of the project, all three teams had tested a number of subjects and collected neural and behavioral data using an RSVP paradigm. To address the third objective, the teams analyzed their experimental data looking for features in the EEG signals that could predict performance errors, that is, either incorrect responses from subjects or errors in classifying subjects' neural signals. Finding reliable, predictive features could have a major impact by enabling new types of robust, adaptive Soldier-system interfaces. The ICB team looked at all trials when the subjects were presented with a target. They compared the instances when the subjects responded correctly ("hits") with those when they didn't ("misses"). They found that they could correctly classify these two categories at a level above chance based upon features of the post-stimulus EEG signal. The SAIC team looked at the temporal dynamics of the score from SAIC's real-time EEG classifier and found a feature that indicates when the system is performing well and classifying accurately. The ARL team looked at the relationship between a subject's behavioral reaction time in an RSVP visual target detection task and their EEG signals. They found a significant difference in the evoked neural response from the trials with the slowest reaction times and those with the fastest.

4.4 Objective 4: Integration of an RSVP Application at ARL

ARL and SAIC worked together during the first quarter of this year to duplicate key components of the SAIC real-time system at ARL. SAIC delivered a database of video clips from the DARPA CT2WS program and supported the ARL scientists in duplicating the CT2WS RSVP experiments with that data. The ARL team then conducted several studies with this implementation. Study results are summarized under Objective 3.

As the project transitions from prototype to integration with the crew station simulator, it is important to use a common set of performance metrics to measure improvements and highlight problems. The metrics quantify the performance of a system that incorporates RSVP and the classification of neural signals to identify targets of interest in imagery. These metrics will be used in the next two years to measure the improvement in performance as research results are incorporated in the prototype system. The metrics will also be utilized to answer the fundamental question of this research for different systems: does the integration of neural-based processing in a given system significantly improve its overall performance? The metrics defined address this question in terms of accuracy, sensitivity, and throughput.

Table 2 summarizes the effort in Year 1 for each of the four objectives. It cross references these objectives to the tasks and milestones.

Table 2. Cross-reference objectives to tasks and milestones and Year 1 status.

Objective	Tasks	Milestones	Performers
1: RSVP Parameters	1.1, 1.7	2, 4	ICB, SAIC, ARL
2: Dual-task	1.4, 1.6, 1.8	4	ICB, SAIC
3: Attentional State	1.1, 1.2	3, 4	ICB, SAIC, ARL
4: Transition to ARL	1.3, 1.5, 1.9	1, 4	ARL, SAIC

5. Parameters to Optimize Performance with RSVP

To address the first objective, the team conducted four separate studies that examined aspects of Rapid Serial Visual Presentation of images. The studies were directed toward how best to present imagery so that a neural signal classifier could accurately detect the viewer’s response.

5.1 Study 1: RSVP Location and Presentation Rate (ICB)

For this study (figure 6a), participants viewed short (approximately 20 items) RSVP streams of letters. In half the streams an X or a 3 was present or absent and at the end of each stream, participants had to indicate whether the target (i.e., an X or a 3) was present or absent. The key manipulation in this task was RSVP rate (8.5 Hz, 10 Hz, and 12.5 Hz) and RSVP distance from the fixation point (0.36°, 0.46°, and 0.73°). The mean percentage of correct responses in this task (i.e., hits and correct rejections) is shown in figure 6b.

5.1.1 Results

The key finding in this study is that there was an interaction between RSVP location and presentation rate, such that when the RSVP stream is presented close to fixation there is no effect of presentation rate, however, a slight shift away from fixation results in a large effect (approximately 15%) on presentation rate. Given that the stimuli in these sequences are highly over learned (i.e., letters), this suggests that moving the RSVP stimuli to the periphery in the context of the SAIC RSVP task may not be effective.

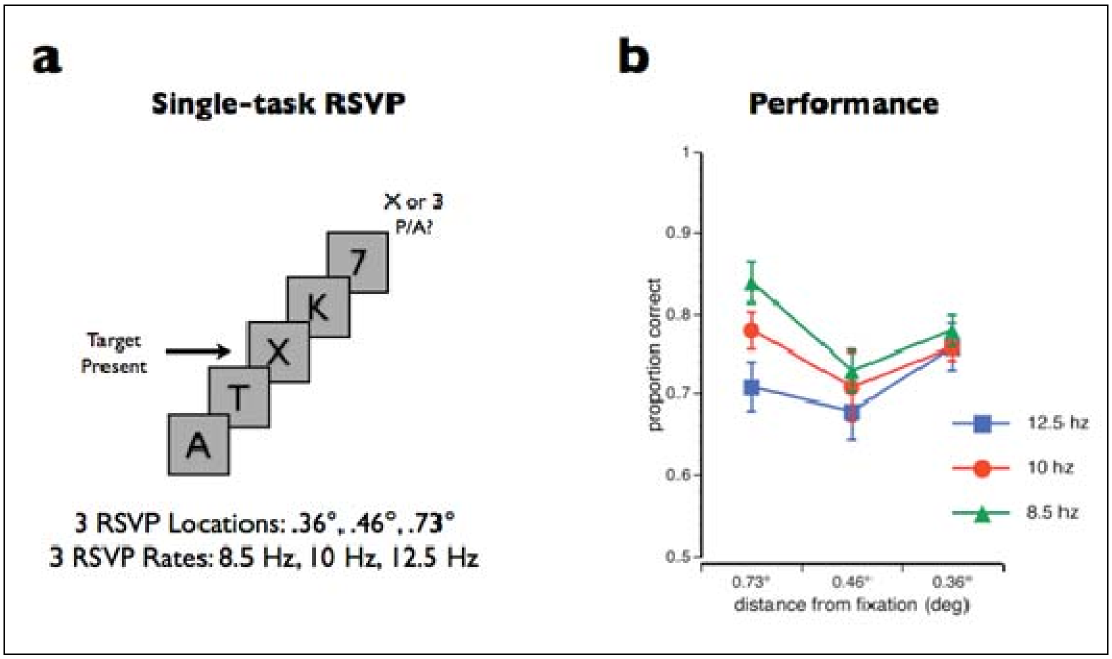

Figure 6. Panel a: Sample stimulus sequence. Panel b: Mean percent correct responses as a function of RSVP rate and location.

5.2 Study 2: RSVP Location and Target Salience (ICB)

The goal of this task was to investigate the role of target salience in two different viewing conditions (figure 7a). In one condition, RSVP sequences of cars were presented in the center of the screen (central task). In the second condition, an RSVP stream of letters was presented in the center of the screen and during that stream a face or a car was presented in the periphery, just above or just below fixation. In each condition, subjects had to indicate whether a face was present or absent. The key manipulation in this study was that target salience was manipulated by titrating the level of noise in the image using a modified staircase procedure. The key measure was the standard deviation of the noise distribution that was required to maintain performance between 75−85%.

5.2.1 Results

The results of this study are plotted as a function of experimental trial in figure 7b and averaged across the experiment in figure 7c. There are three key results. First, overall noise level is lower when the targets were presented in the periphery. Second, maximum noise level peaked at about the same time and at about the same level in both conditions. Third, the drop in noise level was more precipitous in the peripheral condition. Together these results suggest that similar levels of performance may be obtained in central and peripheral tasks, performance in the peripheral task is less robust to targets that are not salient.

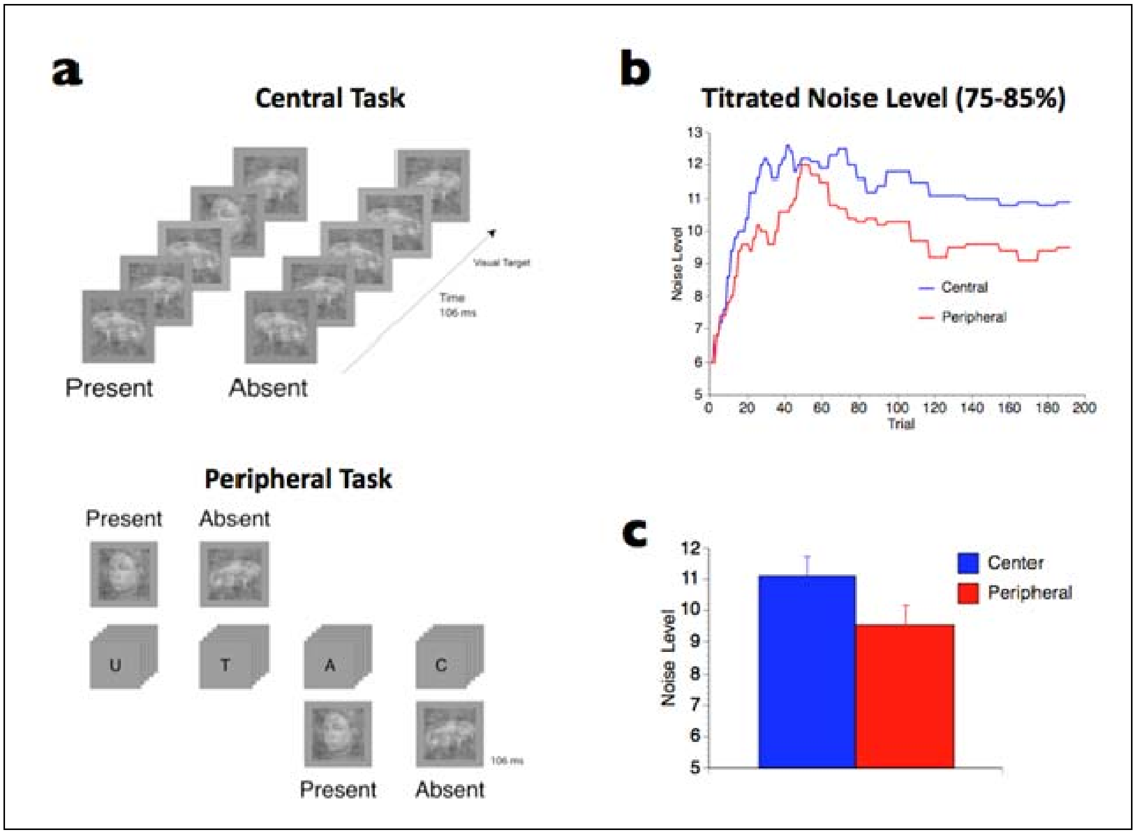

Figure 7. Panel a: Sample stimulus sequences in the central and peripheral tasks. Panel b: Mean standard deviation of the noise distribution required to maintain performance between 75%–85% plotted as a function of trial. Panel c: Same as Panel b, except averaged across the entire experiment.

5.3 Study 3A: Target Frequency (ICB)

The goal of this study was to bridge the gap between the SAIC RSVP task and the tasks we have been using in the ICB 6.1 work. Here we are using the face-car stimuli (Das et al., 2010) with the same timing parameters as those used in the SAIC task. The participant's task was to monitor the sequence for faces and to press the space bar when one is detected. A face occurred only 10% of the time. EEG data from 32 electrodes were collected while subjects performed this task.

5.3.1 Results

Single-trial voltages from the EEG data were submitted to a linear discriminant analysis, similar to what we have used in the past (i.e., Das et al., 2010) and the preliminary results for five observers using one electrode (PO4) are shown in figure 8. There are three key findings. First, classifier accuracy peaks at about 300 ms after the presentation of the stimulus. This can be seen in both the single subject data (Panel A) and in the subject mean (Panel B). Second, there are clear individual differences in classifier performance. Third, the peak classifier performance in this task, in which the probability of a face is 0.1, is approximately 150 ms later than in our recently-published study in which the probability of a face was 0.5 (Panel C, Das et al., 2010). When this difference is considered in light of the SAIC work on target probability (see Study 4), it suggests that target probability is likely a critical factor in determining the spatiotemporal dynamics of classifier performance.

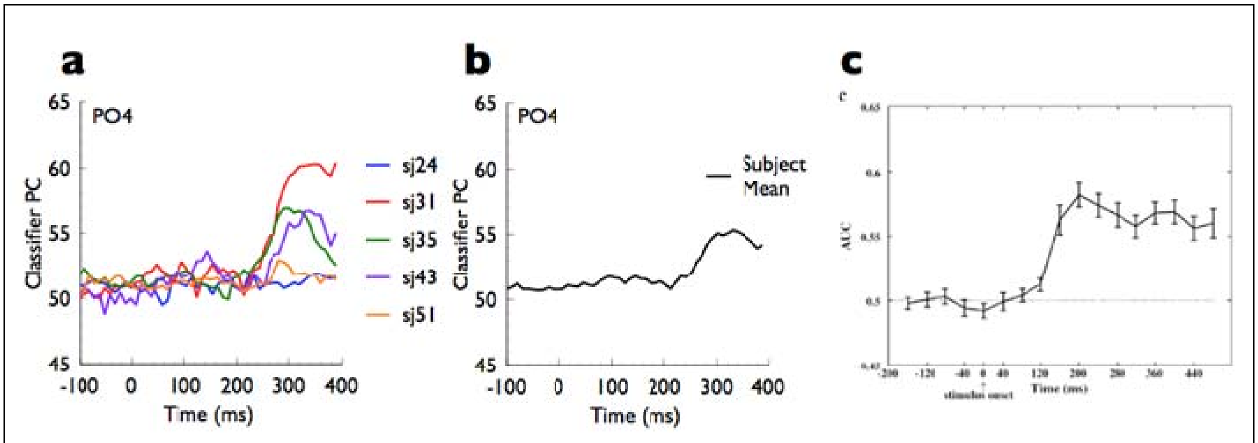

Figure 8. Panel a: Classifier percent correct for each observer using EEG amplitude at electrode PO4 plotted as a function of stimulus onset. Panel b: Classifier performance averaged over subjects. Panel c: Classifier performance from Das et al., (2010) in which the probability of a face as 0.5.

5.4 Study 3B: Target Frequency (ICB)

Based on the results of Study 3A, this study tested the hypothesis that target probability is likely a critical factor in determining the spatiotemporal dynamics of classifier performance by conducting a multi-session experiment in the RSVP task (2 Hz) in which the target was a face and the nontargets were cars (both were embedded in noise). Each observer participated in four sessions. In each session, only the target probability was manipulated: with values of 0.05, 0.10, 0.25, or 0.50 randomly assigned to each session. A total of eight subjects completed four separate sessions (32 total sessions), where each session differed in terms of the probability that a target was presented.

5.4.1 Results

The behavioral performance (d') for all participants is shown in figure 9 as a function of target probability. Clearly, sensitivity to the target declines as a function of increasing target probability.

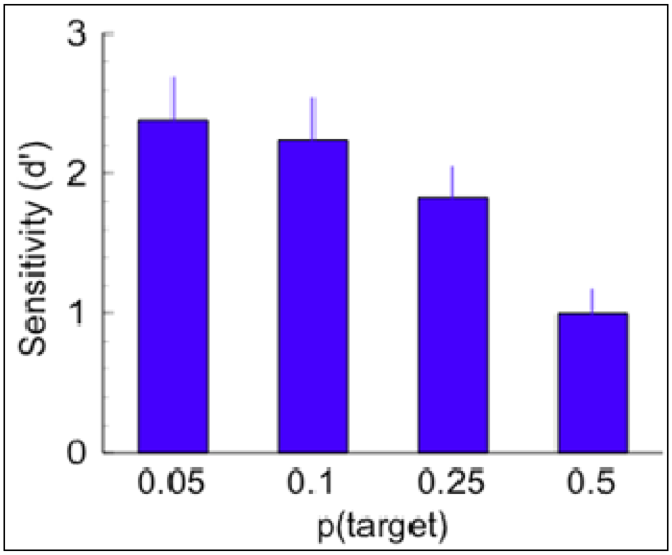

Figure 9. Behavioral performance (d') plotted as a function of target probability averaged across all observers (n=8).

Shown in figure 10 are the results of a new pattern classification approach, which identifies the optimal spatial features that carry the most discriminative information for the particular classification problem in question. The resulting mean spatial filters are plotted as a function of target probability in figure 10. Visual inspection of the spatial filters indicates that as target probability decreases there appears to be an increase in the distribution of discriminative information across the parietal and occipital electrodes. Under high probability conditions the most discriminative information appears to be largely isolated at lateral occipital electrodes.

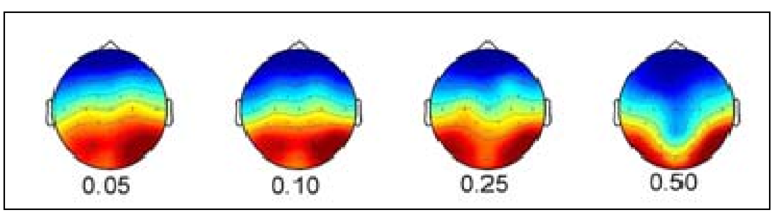

Figure 10. The mean spatial filters depicting the source of discriminative information between targets and nontargets as a function of target probability.

To demonstrate that the pattern observed in the average spatial filters is not driven by a small number of subjects, the spatial filters for each subject are plotted for each condition in figure 11. All but one subject (S8) shows the same trend for a more diffuse distribution under low target probability and more focused lateral occipital distribution at high target probabilities. The results of both the group mean and single subject data clearly indicate that the optimal electrodes for target classification changes as a function of target probability. Thus, if the target probability is known for a specific task context, then the classification algorithm could be optimized to emphasize the appropriate electrodes for that condition.

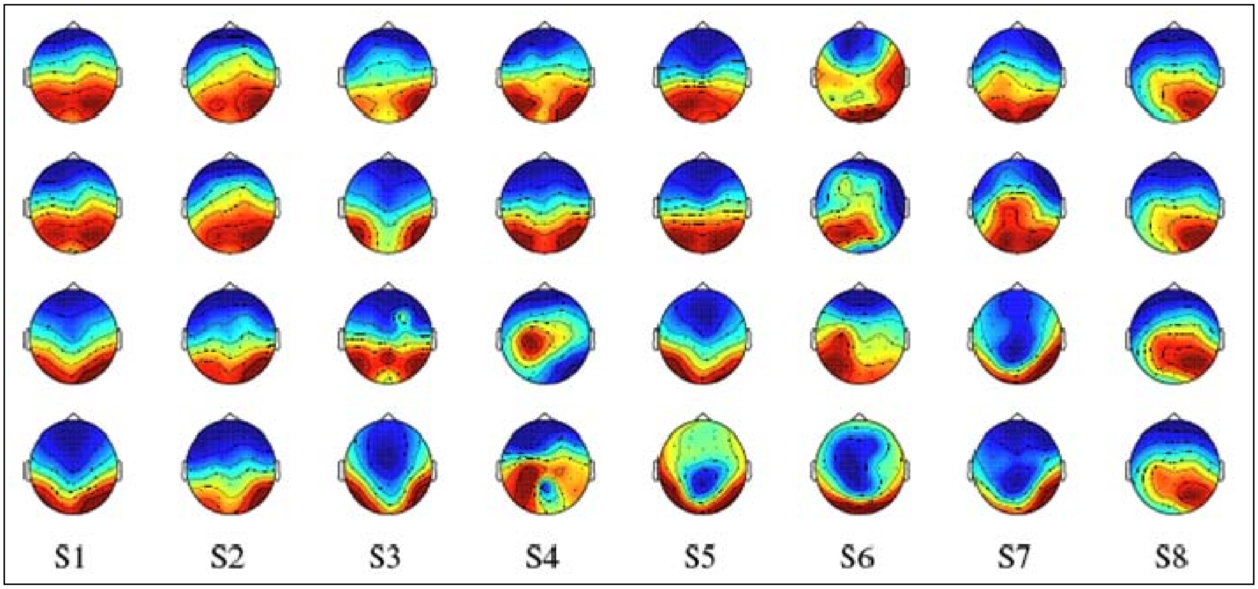

Figure 11. The spatial filters for each individual subject depicting the source of discriminative information between targets and nontargets as a function of target probability (top – bottom rows = 0.05, 0.10, 0.25, and 0.5, respectively).

After the spatial filters were constructed, target classification was performed. We have adopted a variant of the linear discriminant analysis (LDA) approach to classification that is based on Bayes Theorem. The results shown in figure 12 are focused on the classification of the stimulus using the first 500 ms of stimulus-evoked EEG activity. Each figure shows the ROC curves for each subject (colored lines) and group average (black line) and associated Area Under the Curve (AUC) in each target probability condition. There are two interesting results from the ROC analysis. First, the overall (AUC) is best when the target probability is 0.10 or 0.25. Second, there appears to be a large amount of variability across individuals. The source of these individual differences is interesting both from a basic science and applied science perspective and it is something that we are currently investigating further with subsequent analyses.

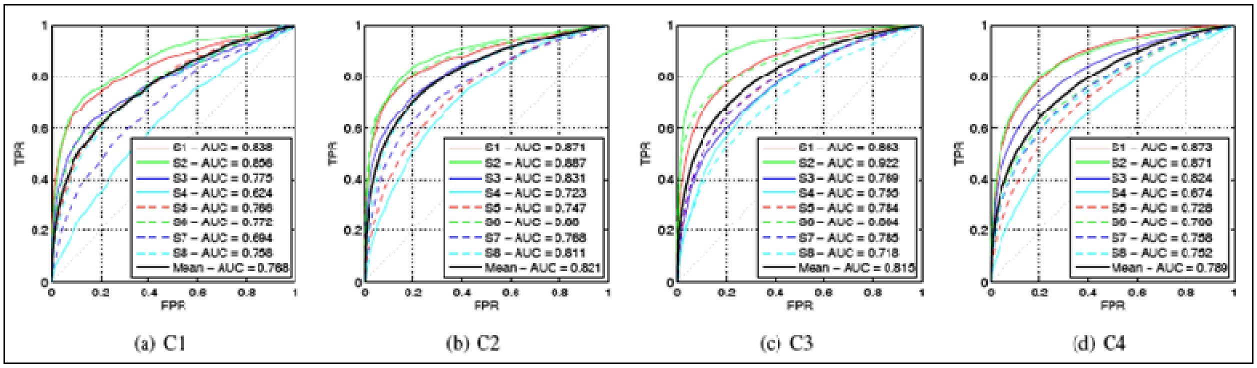

Figure 12. Pattern classification ROC curves plotted as a function target probability. Colored lines represent each subject, the black line the group mean. Panels a–d show the results for each target probability condition 0.05, 0.10, 0.25, and 0.50 (C1–4, respectively). TPR=True Positive Rate, FPR=False Positive Rate.

Because target probabilities vary across task contexts, it is important to know how robust a classification model is with respect to changes in target probability. To investigate this issue, we ran several analyses where the pattern classification algorithm was trained on one target probability condition and tested on the remaining three conditions. The ROC curves for each of these analyses are shown in figure 13. There are two interesting results. First, there is an overall reduction in classification AUC for all training conditions. Second, the best performance was obtained when the classification algorithm was trained on the 0.5 probability condition. This contrasts the previous analysis which trained and tested on the same condition and suggests that when a target probability is unknown that using the higher probability condition may be the best option.

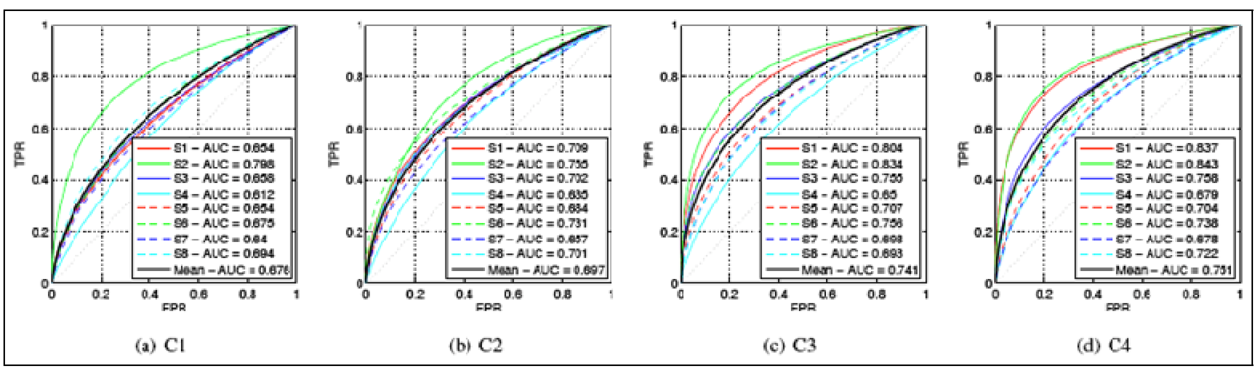

Figure 13. Similar to figure 12, except when training on one condition and testing on the remaining conditions.

5.5 Study 4: Target Frequency (SAIC)

For this study, SAIC leveraged an extensive dataset collected during the CT2WS project, both in the laboratory and in field tests, to focus on parameters that affect classification performance in the SAIC real-time system. This was of particular interest since we observed a decrease in performance for the same subjects in the field test as compared with the laboratory. The results of neural signal classification were significantly less accurate in the field. One factor that quickly emerged was the difference in target probability. In the lab, target probability was pre-selected and fixed. In the field sessions, target probability varied greatly.

Figure 14 illustrates the difference in target probability between a lab and field experiment. The first two rows show the classifier scores and average target event related potential (ERP) for a laboratory experiment. The second two rows show the same data from the field experiment. There was a clear difference in target probability (i.e., the ratio of red diamonds to black circles per unit of time) between these experimental sessions. While the lab session had a constant target probability the field session varied form very low to very high target probability. The resulting effect on the ERP is clear, showing a significant degradation in field ERP.

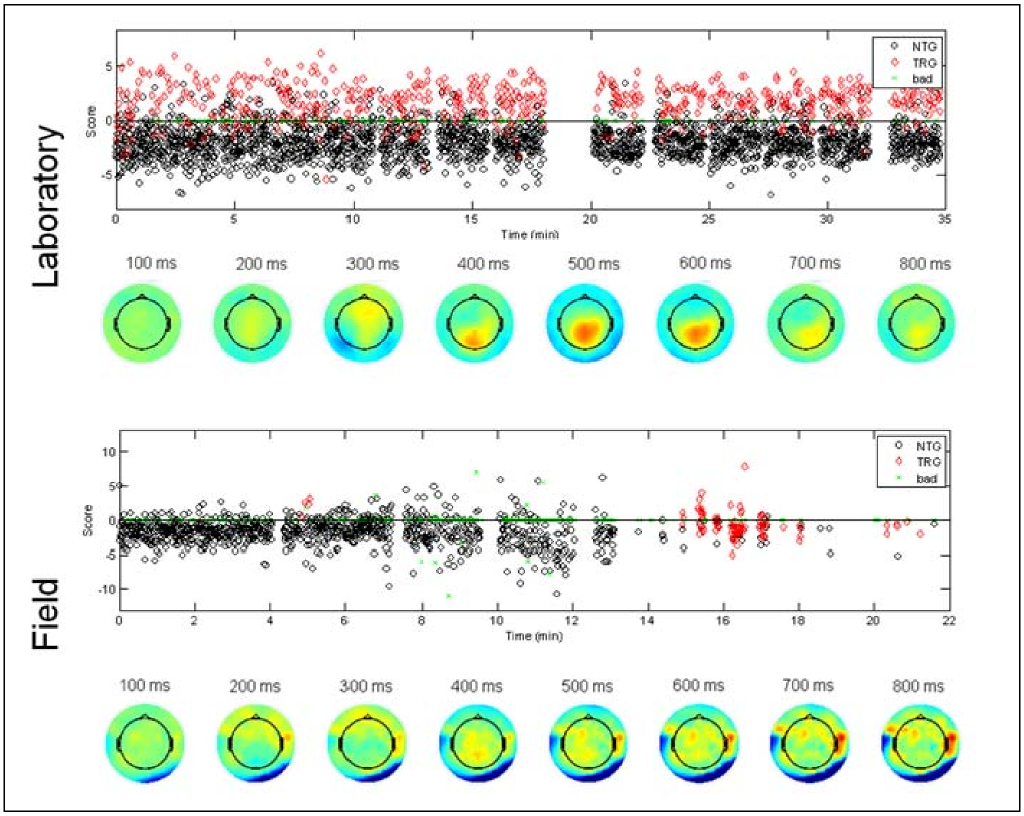

Figure 14. Automated neural processing system comparison. Top rows represent one experimental session, bottom rows represent one field session. Scatter plots show the classifier score for each stimuli as a function of time (NTG = non-target, TRG = target). Bad events are when the EEG could not be classified due to artifact or noise. The topographic plots are average target minus non-target ERP over the entire session.

5.5.1 Results

If we focus on the Field scatter plot in figure 14, it is clear that when the target probability was high, during the second half of the test, the target scores were low (below the threshold of 0) and thus, many targets were misclassified by the system as nontargets. In general, as target probability increased the average classifier score decreased, for both targets and non-targets (figure 15). This resulted in a decrement in overall classifier performance for those sessions. However, with knowledge of target probability, the classifier score can be adjusted to offset the decrease. Figure 16 illustrates how correcting for target probably increases performance. Of course, an operational system will not have access to true target probability; however, target probability can be predicted directly from the score distribution. Specifically, target probability is inversely related to the kurtosis of the scores. A system that continuously monitors recent classifier scores would likely be able to estimate target probability.

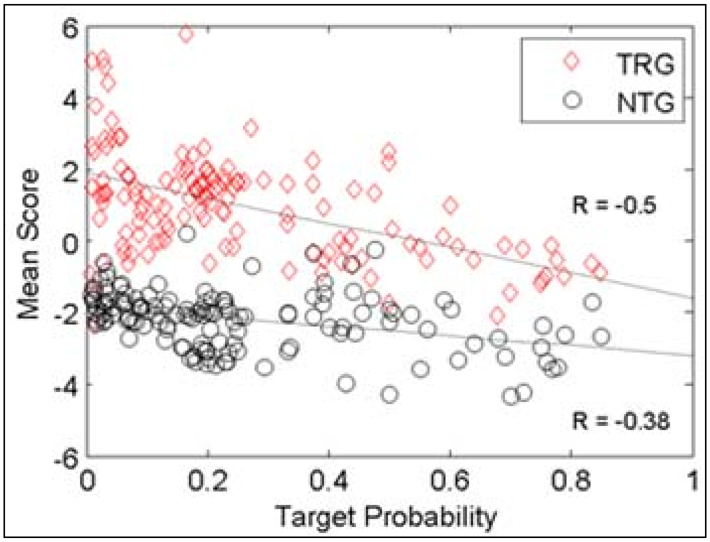

Figure 15. Classifier Score and Target Probability. Average score, calculated over 2-min epochs, plotted as a function of target probability within that epoch. TRG scores in red, mean NTG scores in black. R values indicate correlation coefficient.

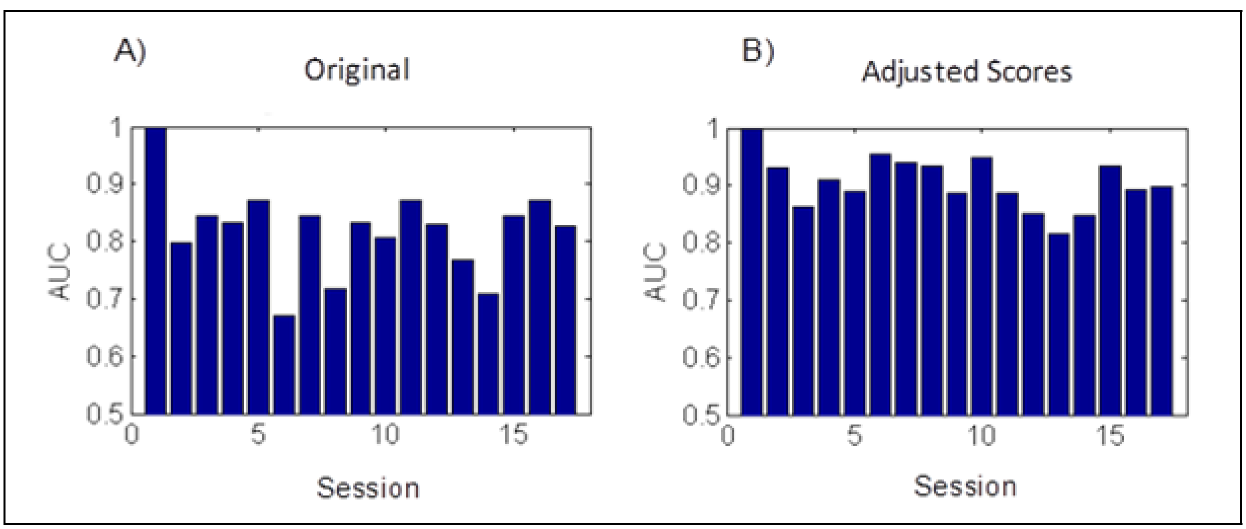

Figure 16. Classifier performance (area under the ROC curve) from the CT2WS field test. Panel a shows the original results while Panel b shows the results if the classifier scores are adjusted based upon target probability.

6. Understanding Dual Task Performance

To meet the second objective, to examine performance when RSVP is carried out in conjunction with a second task, the team developed a dual task experiment that included visual target detection with RSVP and a simultaneously occurring auditory task. SAIC and the ICB each used their respective RSVP tasks and added a primary task of listening for a call sign. For the ICB, the visual targets were faces or cars. SAIC used the video imagery from CT2WS. The motivation for this specific dual-task paradigm was twofold. First, both the visual and auditory task are akin to something a Soldier would be doing while interacting with a crew-station system. Second, evidence suggests that performance degradation from cross modality multitasking is much less than multitasking in the same modality (Alais et al., 2006). Most all studies of RSVP have been structured so that the RSVP is the central and only task. Two studies were carried out to examine RSVP with an auditory task.

6.1 Study 5: Guidelines for Dual Tasks (ICB)

In this study, the visual RSVP task consisted of the target (a face) presented with 0.10 probability in a 2-Hz RSVP of cars. Additionally, auditory two-syllable words selected from the military alphabet, presented using text to speech functions, are played through speakers simultaneously with every sixth image. When performing the word detection task, a target word was randomly selected at the beginning of that session that occurred with a 0.10 probability. Participants performed three different conditions: face detection only, word detection only, or simultaneous dual detection. Order was randomized, but restricted so that the word detection only condition followed either face detection only or dual task, thus ensuring that participants were practiced in face detection before performing the word task in isolation. This task was designed to mimic a task Soldiers may do when monitoring auditory communications for their call sign.

6.1.1 Results

Seventeen participants completed this study. Overall behavioral performance is shown in figure 17. The only significant effect on performance was the difference between the auditory and visual tasks. There was no significant dual-task impairment.

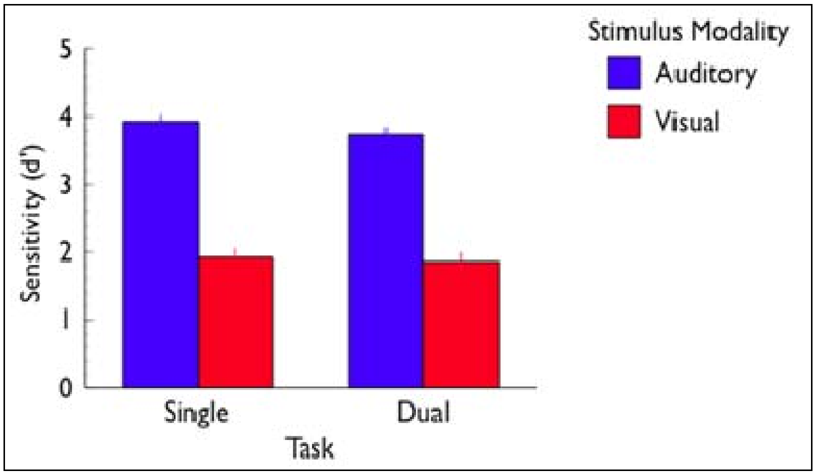

Figure 17. Behavioral performance (percent hits and percent false alarms) plotted as a function of the number of tasks and task type.

The results of the pattern classification analysis using linear discriminant analysis are shown in figure 18. It is important to note that this analysis is focused on using neural activity to predict whether a face was present in the visual stream in the conditions in which the observers were performing on the auditory task alone (auditory single), both tasks (visual dual), or the visual task alone (visual single). There are two key results that emerged from this analysis. First, the performance of the classifier was unaffected whether performing the visual task alone or while performing both the auditory and visual task. Second, performance of the classifier is severely impaired when subjects are instructed to perform the auditory task only. These results suggest that the real time classifier may only be successful under multi-task conditions when observers are told to actively attend to the visual task.

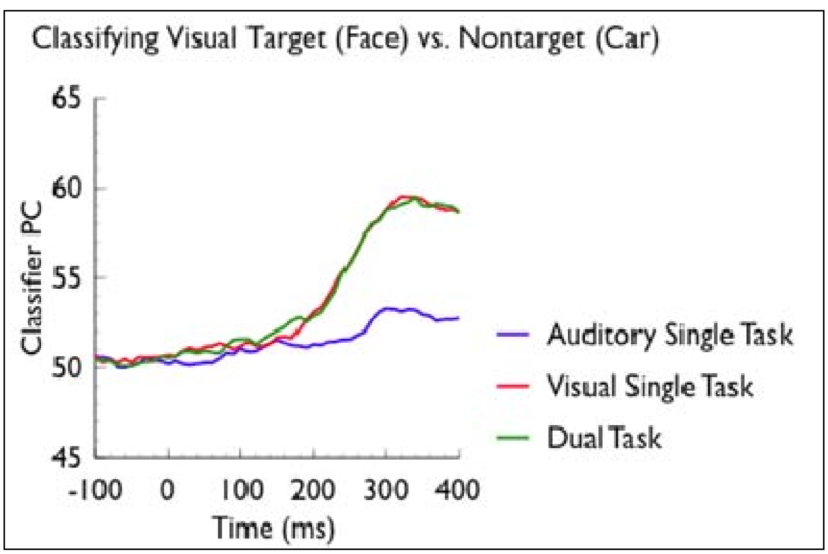

Figure 18. Pattern classifier performance decoding the visual stimulus plotted as a function of time and task condition.

In addition to the pattern classification analysis described above, we have also performed a series of correlations between behavioral performance and classifier performance. This analysis revealed significant positive correlations between classifier performance and behavioral performance in both the single and dual task conditions (figure 19: Panels A and B). Moreover, a correlation between the classification performance in the single task condition and classification performance in the dual task condition was also significant (figure 19: Panel C). These results suggest that the classifier can be used as a proxy for human performance in different task conditions and that the classifier in one task context can serve as a performance proxy for classifier performance in a different task context.

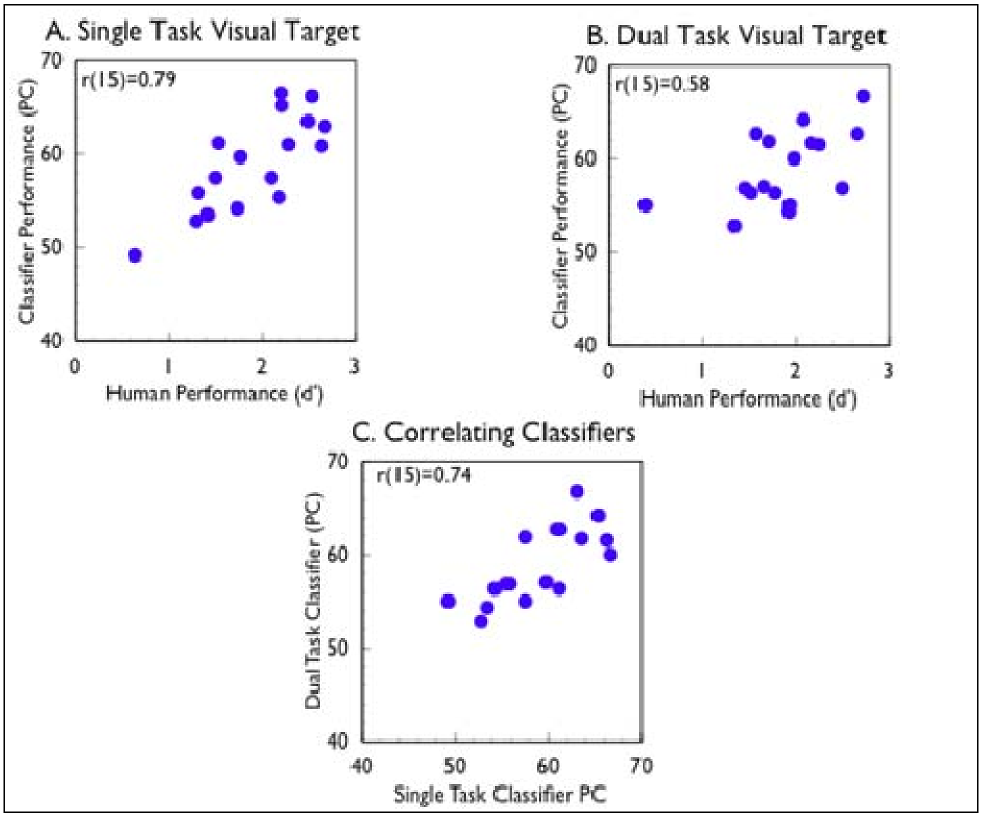

Figure 19. Correlations between behavioral performance and classifier performance in the single (Panel a) and dual (Panel b) task conditions and between single and dual task classifier performance (Panel c).

In addition to this analysis, a second type of classifier was applied and the results analyzed. The second classifier was the LDA classifier described in the previous study. This first set of analyses focused on classification of the visual stimulus under single and dual task conditions and classification of the auditory stimulus under single and dual task condition. The results of this analysis are plotted in figure 20 and in table 3. Interestingly, the AUC when classifying the visual stimulus is unaffected by the dual task manipulation, but the AUC classifying the auditory stimulus is impaired under dual task conditions relative to single task conditions.

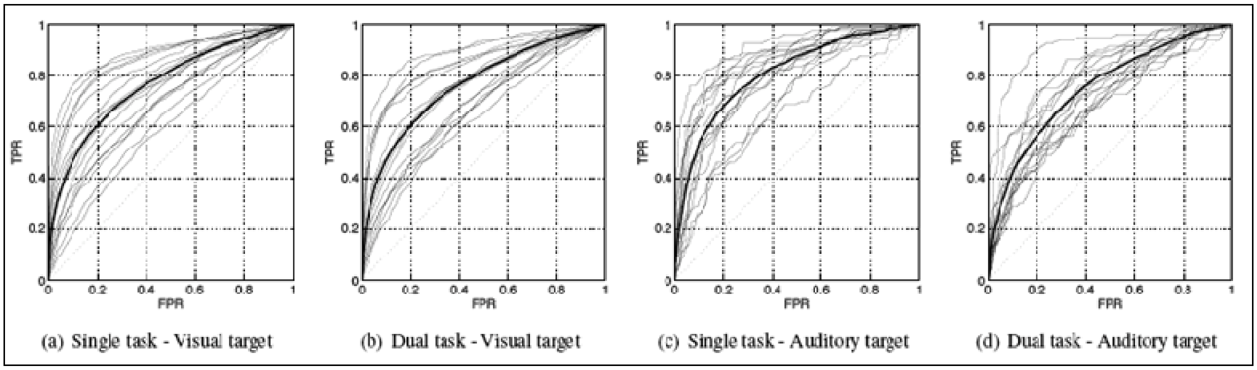

Figure 20. Pattern classifier ROC curves when decoding the visual and auditory stimuli. Gray lines are for individual subjects. The black line indicates the group mean.

Table 3. Classifier AUC as a function stimulus (Vis./Aud.) and number of tasks (Single/Dual).

	Vis. Single	Vis. Dual	Aud. Single	Aud. Dual
Mean	0.758	0.759	0.809	0.751
SD	0.093	0.086	0.073	0.069
Max	0.889	0.896	0.906	0.915
Min	0.585	0.624	0.666	0.676

A follow-up analysis was performed training the classifier on one task (e.g., single) and then testing it on another task (e.g., dual) within each stimulus modality. In all cases, classification was well above chance, but significantly degraded when testing on data that contained a different number of tasks.

We also conducted analyses that revealed significant positive correlations between individual differences in classification accuracy under single task conditions with individual differences in classification accuracy under dual task conditions. The key result was that within each modality there were significant correlations between single and dual task classifier performance. The visual task correlation was the best at $r(15)=0.89$. The auditory task correlation coefficient was much less robust, but still significant at $r(15)=0.55$. Together these analyses suggest that although there is degradation in classifier performance when training on one task and testing on the other, one could still potentially predict the performance in one condition using performance in the other condition, particularly for the visual task.

6.2 Study 6: Guidelines for Dual Tasks (SAIC)

SAIC's dual task was an extension of the RSVP paradigm used in the CT2WS program. Specifically, 500-ms video sequences were presented in a serial and uninterrupted fashion for a number of 2-min blocks. Subjects maintained fixation on the video stream and pressed a button if they saw a target (e.g., person or vehicle). In addition to this visual task, subjects were simultaneously listening to a communication channel of spoken words (military alphabet). They were instructed to push a second button if they heard specific target words or call signs (e.g., “november,” “zulu”).

6.2.1 Results

Behavioral results from our dual task experiment indicate that the majority of subjects can perform both tasks with reasonable accuracy. However, even in this relatively simple multitasking scenario, the addition of the auditory detection task significantly affects the reaction time in the visual (RSVP) task. Figure 21a shows the relationship between stimulus onset asynchrony (SOA), the time difference between the visual and auditory presentation, and the reaction time (RT). Here, the reaction time is delayed as the SOA approaches the average response time (about 500 ms) for visual target detection. This effect is also reflected in the overall reaction time distributions (figure 21b); where the average reaction time for trials with both visual and auditory stimuli (yellow) is faster for trials with visual stimuli alone (blue). This type of behavioral interference is common, even in the simplest types of multitasking (Pashler, 1994).

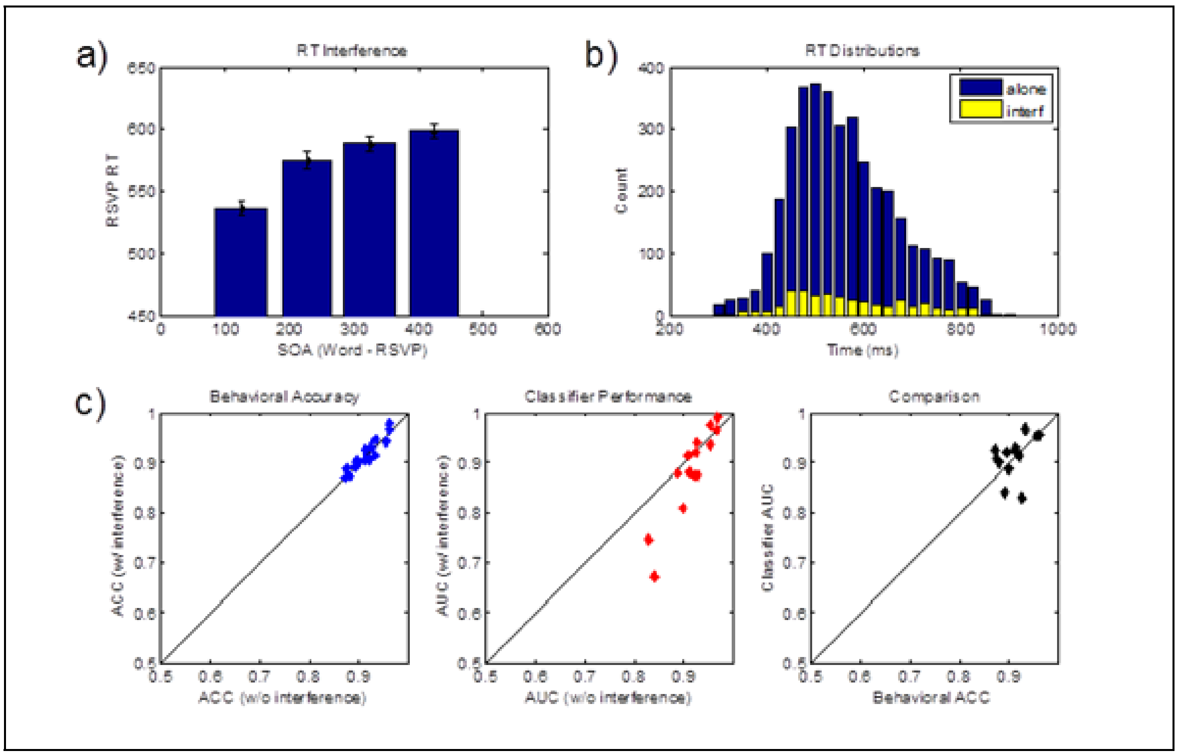

Figure 21. Behavioral and Classifier Performance for Dual Task Experiment (all subjects). The task was to simultaneously detect targets in video imagery and specific words in an audio communication stream. Panel a: The relationship between SOA and RT. Panel b: RT distributions for trials with interference (visual and auditory together, yellow) and without interference (visual alone, blue). Panel c: Behavioral accuracy (ACC) and classifier area-under-the-curve (AUC) with and without interference. Note that interference affected RT but not ACC.

In addition to behavioral interference, we found evidence for interference in the classification of the evoked response (figure 21c). For the majority of subjects, the classifier performed equally well for trials with and without auditory interference. However, several subjects showed a significant degradation in classifier performance for trials where visual and auditory stimuli were presented together. Interestingly, these subjects tended to have relatively lower area under the ROC curve (AUC) values, even without auditory interference, indicating poorer classifier performance. This type of interference could be a consequence of overlap in the evoked response from visual and auditory stimuli. To illustrate this, figure 22 shows that the scalp topology of the auditory (for target words) and the visual (for target videos) ERP. For this subject, there is a noticeable overlap in the response between 600 and 800 ms.

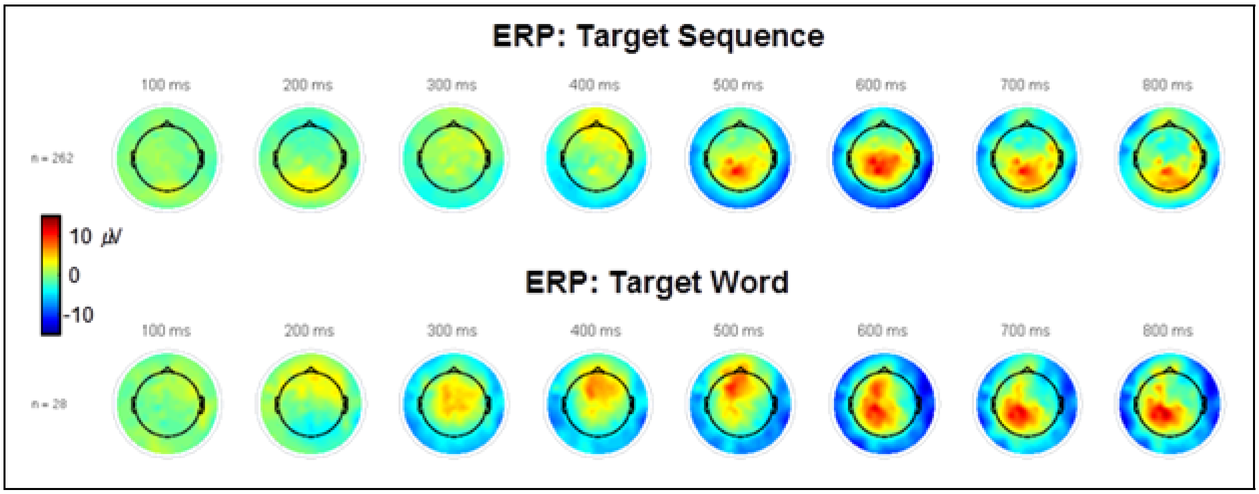

Figure 22. ERPs for Visual and Auditory Targets (one subject). Top row: ERP for video sequences containing targets. Bottom row: ERP for target words.

To compare the overall performance of the visual classifier with the behavioral response we did the following analysis. First we calculated the probability of detection (Pd) for the visual targets based on the behavioral response (figure 23a). We then found the score threshold that resulted in the same Pd from the classifier (numerical threshold values shown in figure 23a inset). Using this threshold we calculated the corresponding false alarm rate (figure 23b). For many subjects the false alarm rate from the classifier was nearly as good as or even better than the behavioral false alarm rate. In addition we calculated the throughput (clips per minute) for each subject (figure 23c). Here the behavioral rate is the true upper bound, denoting the average rate that the subject proceeded through the experiment. The classifier throughput reflects the percentage of these trials that were classified (i.e., free of artifacts). Several subjects in this study had very few artifact trials and therefore maximal throughput. Overall, this result indicates that the current state of artifact detection and mitigation is good, but needs improvement. A *post hoc* analysis (data not shown) indicated that many of these trials could have been successfully scored despite the presence of artifacts.

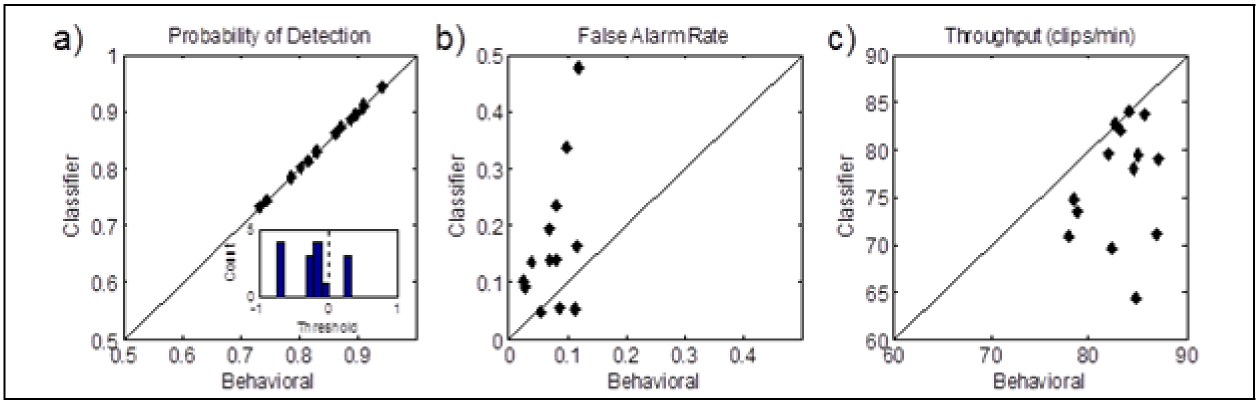

Figure 23. Classifier Performance Summary (all subjects). Panel a: Probability of detection for the classifier is matched to behavior. Panel b: False alarm rates for the matched Pd. Panel c: System throughput (clips per minute), reflecting the percentage of trials classified (i.e., free of artifacts).

The preceding analyses have compared the classifier results with the behavioral response, indicating that, at best, the classifier matches behavioral performance. This result may seem to indicate that EEG classification is no better than a behavioral response. However, the purpose of this experiment was not to "outperform" the subject. Rather, the purpose of this experiment was to see if a neural classification system can continue to perform in a multitasking environment. Moreover, the experiment was not explicitly designed to be difficult. The rate of the video clip presentation was slow enough (2 Hz) for the subject to respond. Together, the above results lay the groundwork for a system that could enhance overall performance, either by increasing RSVP presentation rate or allowing the subject to focus on responding to the auditory (or other) task alone.

7. The Neural Correlates of Attentional Impairment

To address this objective, the three teams analyzed their experimental data looking for features in the EEG signals that could predict performance errors, that is, either incorrect responses from subjects or errors in classifying subjects' neural signals. Finding reliable, predictive features could have a major impact by enabling new types of robust, adaptive Soldier-system interfaces.

7.1 Study 7: Predicting Hits and Misses (ICB)

In Study 3B, a total of eight subjects completed four separate session where each session differed in terms of the probability that a target was presented. In this case, the target was a face and the nontargets were cars (both were embedded in noise). The goal of Study 7 was to analyze the data to see if a classifier could differentiate the trials in which the subjects correctly detected a face (hits) from those in which they did not detect the face (misses). In the initial analysis, we used an LDA-based classifier with temporally windowed EEG amplitude data. The results are shown in figure 24. The peak classifier performance was within the 250−400 ms time window and the best classification occurred when the target probability was 0.5. While this may reflect an important difference between hits and misses as a function of target probability, it must be interpreted with caution because there are also more trials that are included in the classification analysis in that condition.

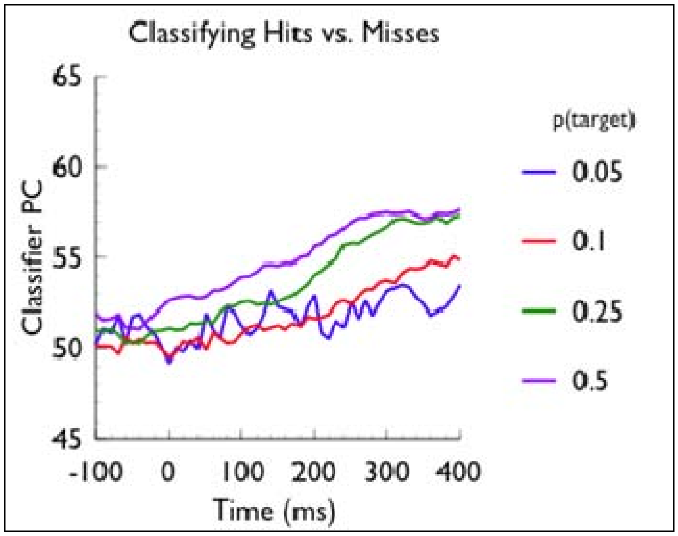

Figure 24. Pattern classification performance for discriminating hit trials vs. miss trials plotted as a function of time and target probability.

We analyzed performance in more detail by attempting to characterize the features of the EEG signal that best discriminated between hits and misses. In this analysis, we constructed three different classifiers, one that was trained on the amplitude of the EEG data, one that was trained on power in specific frequency bands, and one that was trained using both amplitude and power. The results of this analysis are shown in figure 25. As with the analyses described above, classification performance declined with increasing target probability. This was true regardless of the type of input. Performance was lowest when classification was based on power alone. At low target probabilities there was a trend indicating that the amplitude only classifier was best, but at high target probabilities there was a trend indicating that the amplitude plus power model was the best. It must be emphasized that these are merely trends and not statistically significant.

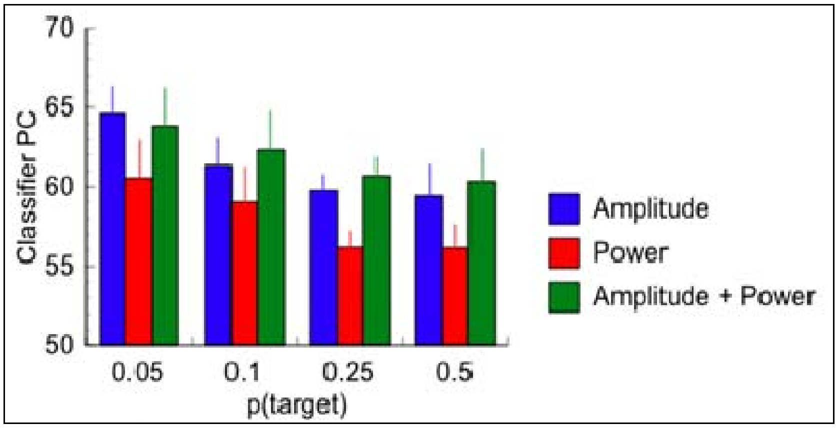

Figure 25. Pattern classification accuracy for discriminating hits from misses when using EEG amplitude only, EEG power in alpha, theta, beta, and delta, or a combination of amplitude and power.

7.2 Study 8: Predicting Classifier Failures (SAIC)

In this study, we analyzed the CT2WS data looking at the temporal dynamics of the classifier score. Results from Study 4 indicated that target probability has a dramatic effect on classifier score. We hypothesized that whatever condition leads to mis-classification (attentional state, temporal lag, internal or external noise, etc.) would be reflected in the temporal dynamics of the score. To examine this we used the subject's customized classifier model to calculate the score of each trial at various time offsets ("lags") before and after the presentation of the stimuli (±160 ms). We then sorted these scores into target and non-target trials. For target trials we recorded the temporal offset between of the peak (highest) score and stimulus onset. Likewise, for non-target trials we recorded the temporal offset of the trough (lowest) score and stimulus onset. Figure 26a shows the standard score distribution as a function of this lag index for both target and non-target trials. Interestingly, the closer the extreme score (peak or trough) is to the stimulus onset the better the classification accuracy. To quantify this in terms of performance, we recalculated the AUC for trials with small absolute lag values (figure 26b). This significant improvement was consistent over the population (figure 27).

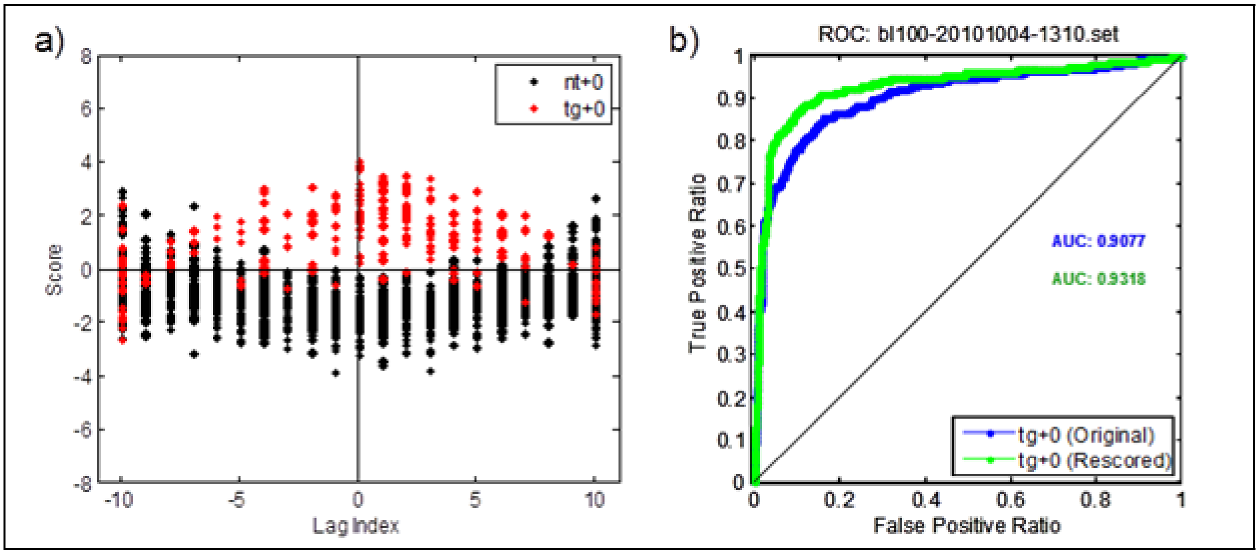

Figure 26. Temporal Dynamics and Classifier Accuracy (one subject). Panel a: Classifier score as a function of lag (see text). Panel b: ROC curves for all trials (blue) and trials with near-zero lag values (green).

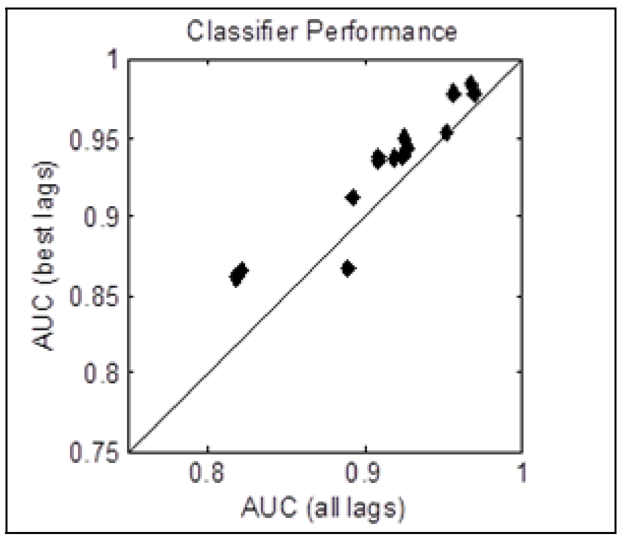

Figure 27. Classifier Accuracy Improvement (all subjects). AUC values for all trials (all lags) and trials with near-zero lag values (best lags).

While taking into account the temporal dynamics of the classifier score does lead to improved accuracy, it does not identify the underlying reason for the improvement. Misaligned trials (i.e., nonzero lag index) could be caused by some internal brain state such as attentional or preparatory state (Kim et al., 2007; Mathewson et al., 2009). Alternatively, they could be caused by some noise source (environmental, subject movement, etc). However, the temporal dynamics in the score are most likely due to the natural variability in the evoked (P300) response. This variability is also reflected in the reaction time (see Study 9). Further analysis of the evoked response is necessary to understand the source of this phenomenon.

7.3 Study 9: ERP Latency and Reaction Time (ARL)

This study focused on neurobehavioral correlations from data acquired from 12 subjects during an RSVP paradigm used in the CT2WS program. The analysis focused specifically on the relationship between target reaction time and P3 peak latency. Many target classification algorithms use features associated with the P3; however, it is unclear what effect if any the latency of this component may have on classification accuracy.

Target images were reviewed prior to experimentation for target detection difficulty. Targets that were partly occluded or difficult to detect were excluded from presentation. Target Response Times (RTs) were divided into quartiles for each subject. We focused on the fastest and slowest performance, which correspond to the first and last quartiles respectively. Quartiles were then used as epoching parameters for the EEG data in order to create averaged ERPs for each subject in each quartile. The top plot in figure 28 shows target ERPs at electrode Pz for the first (red) and last (blue) quartiles as well as the ERPs to non-target stimuli (black) and the average of the first and last quartiles (green). While the first and last quartiles have latency differences beginning approximately 400 ms post target stimulus, early sensory activation cannot account for this relationship; performance quartiles did not change as a function of latency or amplitude in early evoked responses as seen in the first positive peak over electrode Oz.

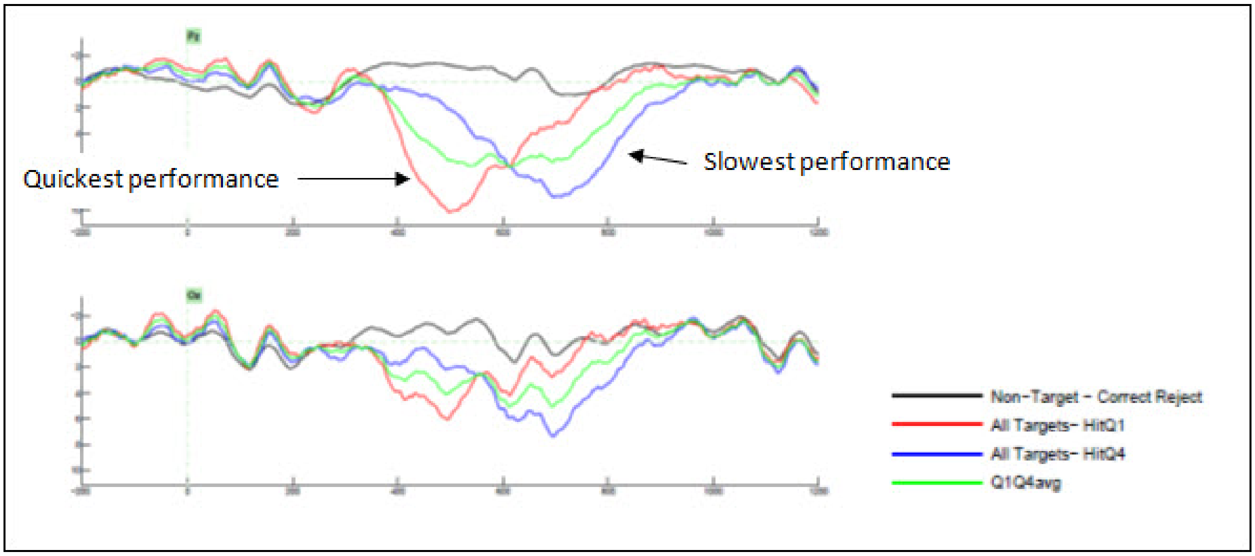

Figure 28. Target ERPs at electrodes Pz and Oz.

Further analysis of the RT and P3 peak latency association revealed a consistent relationship at the single trial level as well as across participants. Figure 29 shows an ERP image plot of all first and last quartile target trials. Trials were sorted by the latency of target reaction time represented by the black line. Figure 30 depicts a significant positive correlation between RT and P3 peak latency.

Neural classification algorithms focusing on P3 amplitude may have increased performance when P3 latency information is also considered. Choosing the peak amplitude of the average ERP response may mask meaningful performance related information present in the dynamic neural activity.

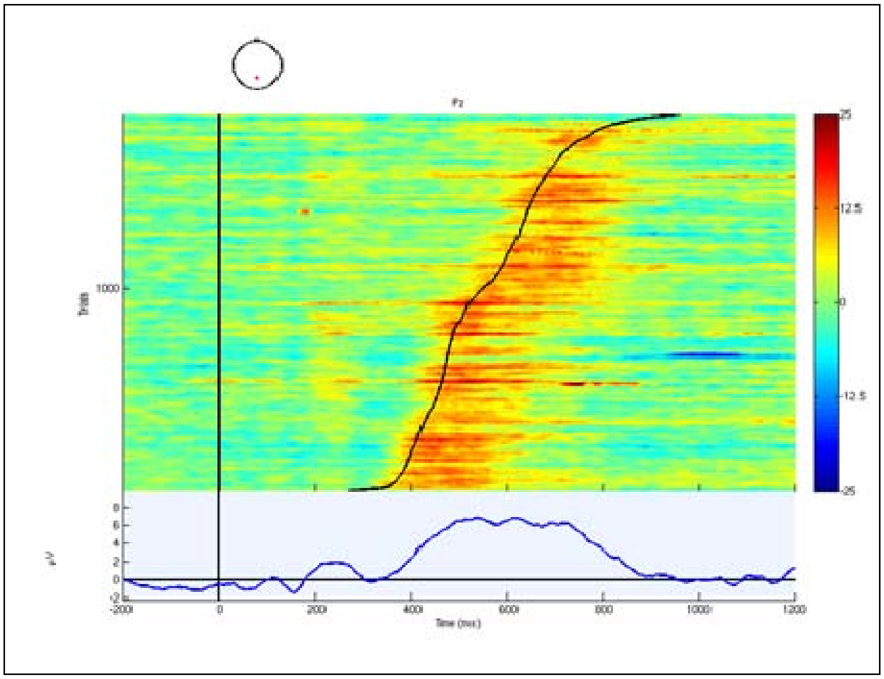

Figure 29. ERP image plot showing the P3 amplitude for each target trial sorted by reaction time performance.

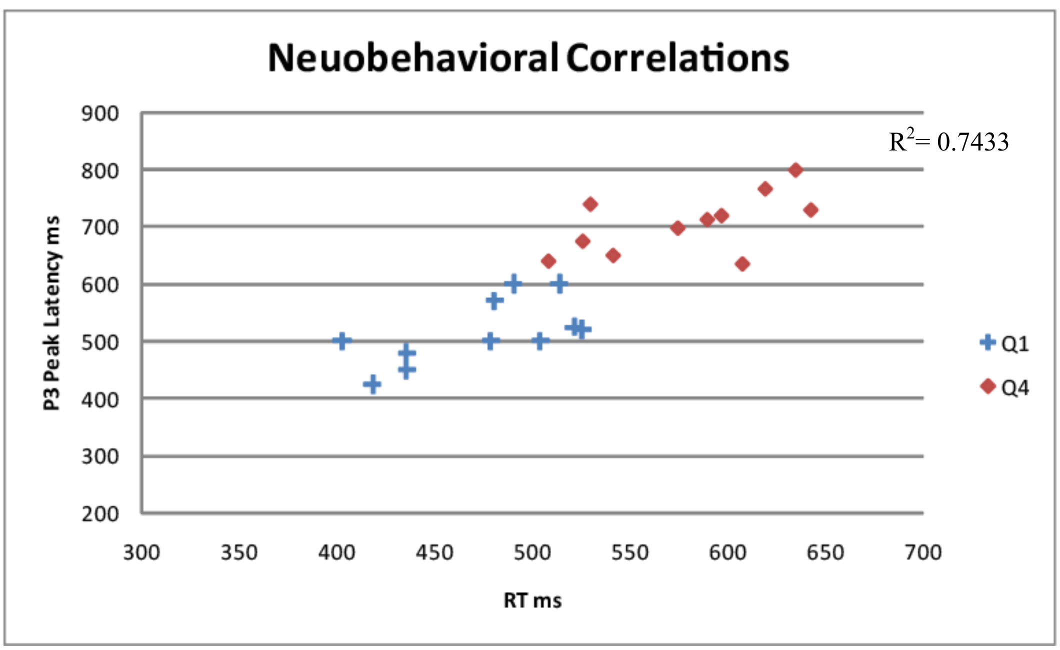

Figure 30. Correlation between RT performance and P3 peak latency. Q1 = first quartile, Q4 = last quartile.

8. Implementation at ARL

This objective to implement components of the SAIC real-time neural processing system at ARL is the first step along the path to transition the results of this project to the Army. Work this year had two parts. First, SAIC provided documentation and support to ARL for their implementation efforts. Second, SAIC defined a set of metrics for assessing the performance of systems that incorporate neural processing. The metrics are designed to support the evaluation of different algorithms and implementations. They will be used to measure improvements in system performance as the results of this research are translated into new methods. We begin with a description of the real-time system and then discuss the metrics.

8.1 The SAIC Real-time System

The SAIC real-time EEG processing system (figure 31) was developed under phase one of the DARPA CT2WS program. The principal goal of this CT2WS system was to rapidly identify a variety of targets over a broad landscape of ground-level imagery by combing the complementary aspects of the computer and human visual system. Computer vision algorithms would initially process the scene; identifying potential targets or threats as regions of interest (ROIs). These small regions would then be shown to the human user under an RSVP paradigm. Finally, the evoked neural response would be used to determine the presence or absences of a threat.

The frontend or computer vision component of this system is not described here. It is assumed that the Experimental Control computer already has a database of ROIs. With this assumed operation of the system then proceeds as follows:

1. The user (or subject) is seated in front of the stimulus display screen.
2. The EEG acquisition system continuously acquires signals from the subject (128 channels at 1 kHz).
3. The subject initiates a session by pushing a button (response pad).
4. A small set (approximately 10) of ROIs are sent to from the Experimental Control computer to the Stimulus Presentation computer and shown to the subject. These ROIs are time-stamped using a synchronizing waveform generated by the EEG amplifier (i.e., universal clock). The time stamps are also inserted into the EEG record for synchronization of the ROI with the corresponding ERP.
5. After each ROI is presented, the Experimental Control computer pulls the corresponding ERP from the EEG Acquisition computer. The ERP is then pre-processed to check for artifacts (eye blinks, subject motion, noise, etc). If the ERP is free of artifacts, a linear

classifier is then used to score the ROI. If the ERP contains artifacts, it is given a null score.

6. ROIs with high positive (target) or negative (clutter) scores are classified accordingly. ROIs with low, ambiguous or null scores are re-cued for subsequent presentation.
7. The Experimental Control computer builds the next set of ROIs, including any ROIs that need to be re-shown (from step 6). These ROIs are then sent to the Stimulus Presentation computer for display.
8. This process (steps 4–7) continues until all ROIs are shown or the subject terminates the session via a button press.
9. Each ROI and corresponding score is displayed for the operator on a results screen that is continuously updated.

The operational progression described above is a high level overview of the real-time system. Details regarding the stimulus content, presentation parameters, classification algorithm, and scoring procedure are provided in a separate document, *Documentation for the SAIC Real-Time EEG System.*

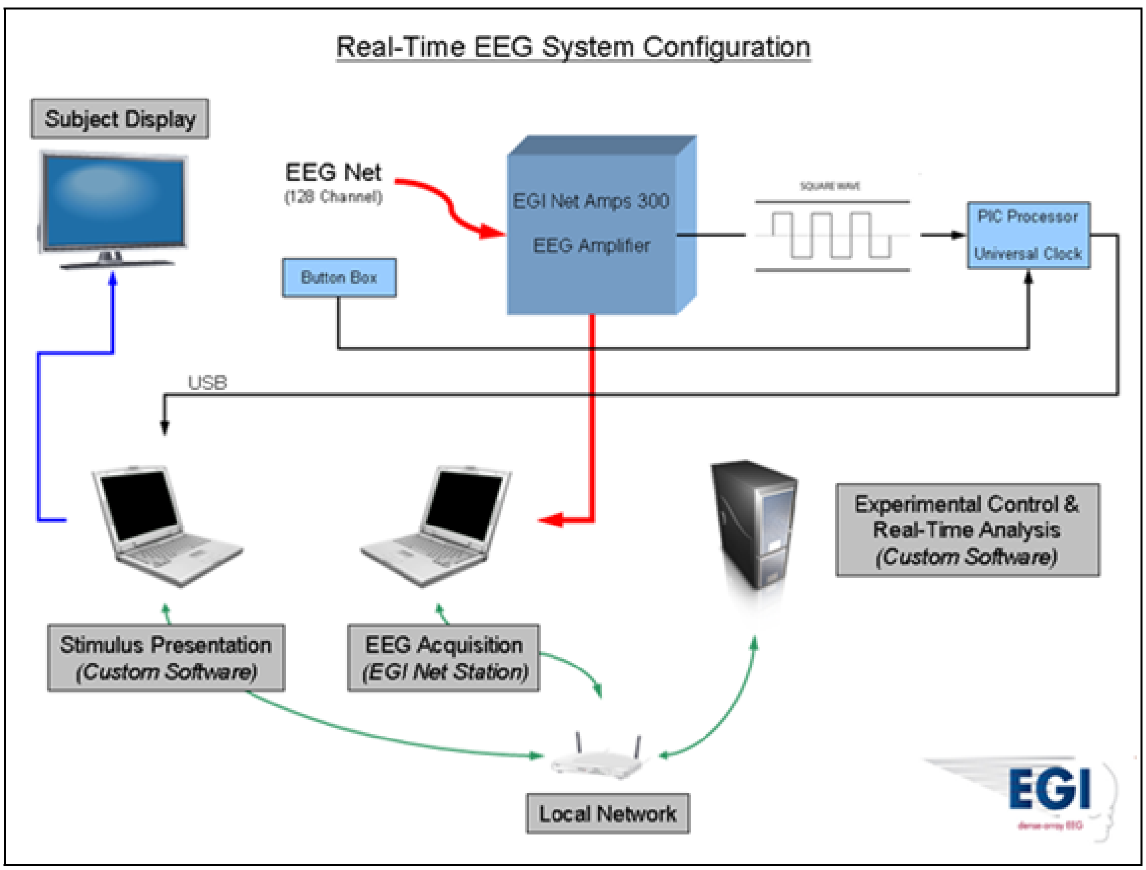

Figure 31. Configuration diagram for the SAIC real-time system.

8.2 Study 10: Metrics (SAIC)

We defined a set of metrics to be used in assessing the performance of a system that incorporates RSVP and neural processing. The purpose of the metrics is to provide a quantification of the improvement, if any, to a system that includes a visual search task such as detecting a target or a threat when that task is performed using neural processing and RSVP. The metrics offer a means to compare performance against a system that does not use RSVP. These metrics will be applied to provide an objective measure of improvement in this project as the prototype under development. As part of this study, we captured baseline metrics for the current system.

Three standard metrics will be used to characterize performance in a system that includes RSVP: probability of detection (Pd), false alarm rate, and throughput. These metrics can be computed for the system with and without RSVP and then compared. Figure 32 contains graphs comparing these metrics for the visual target detection task implemented by SAIC in Study 6. Here the behavioral data comes from the subjects pressing a key when they see a target during the RSVP experiment. In this instance for the behavioral condition, throughput is expressed as the average rate that the subject progresses through the experiment in clips per minute. This is the true upper bound for both the behavioral and automated system. The RSVP system throughput reflects the percentage of these trials that were classified. The system will not classify a response if there are artifacts such as eye blinks or muscle movement reflected in the EEG signal. Several subjects in this study had very few artifact trials and, therefore, maximal throughput. Overall, this result indicates that the current state of artifact detection and mitigation is good, but needs improvement. In examining the trials that were rejected by the system, we found that many of these trials could have been successfully scored despite the presence of artifacts.

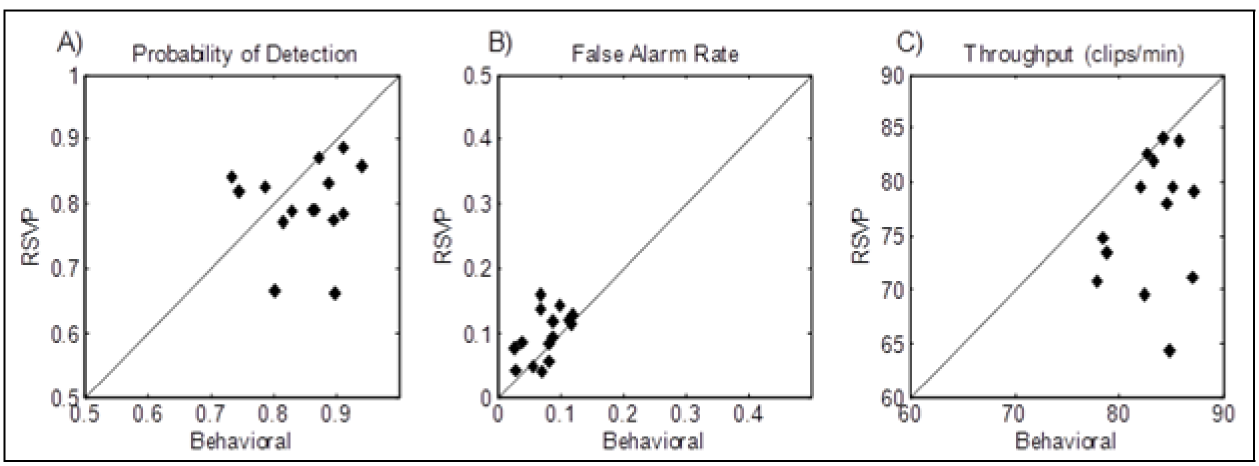

Figure 32. Classifier Performance Summary (all subjects). Panel a: Probability of detection for the classifier is matched to behavior; Panel b: False alarm rates for the matched Pd; Panel c: System throughput (clips per minute), reflecting the percentage of trials classified (i.e., free of artifacts).

The SAIC real-time EEG processing system implements a linear classifier that applies a set of weights (the neural response model) to the values coming from the individual EEG channels to compute a single score, which is then used to classify the response. Thus the classifier produces a score for each stimulus based on the neural response of the subject. A set of metrics for the RSVP system can be computed based on an analysis of the classifier output. One such metric is the area under the ROC curve (AUC) which is standard for characterizing how well an automated algorithm performs, where AUC=1 indicates a perfect system and AUC=0.5 is a system performing at the level of chance. Figure 33 shows a single ROC curve for one subject from Study 6. Figure 34 shows a chart with the AUC for all subjects.

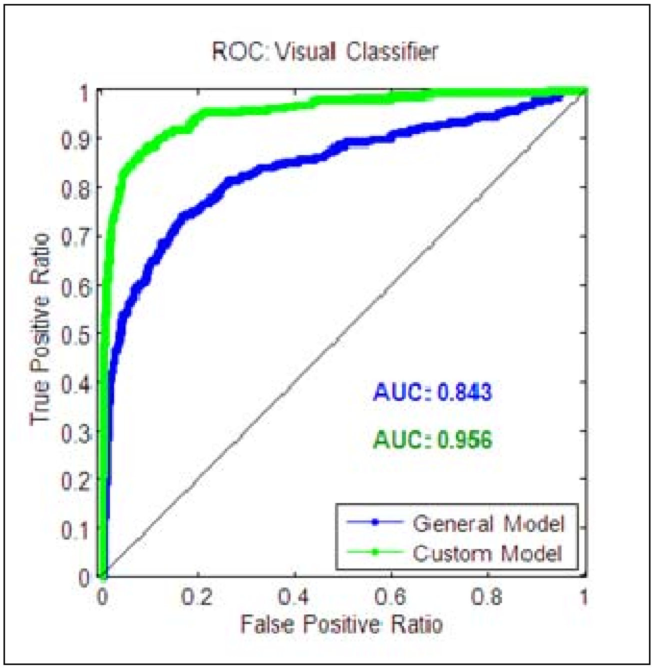

Figure 33. ROC curve for a single subject for classifier scores generated using a general neural response model (in blue) and for scores generated by using a model built for this individual (in green).

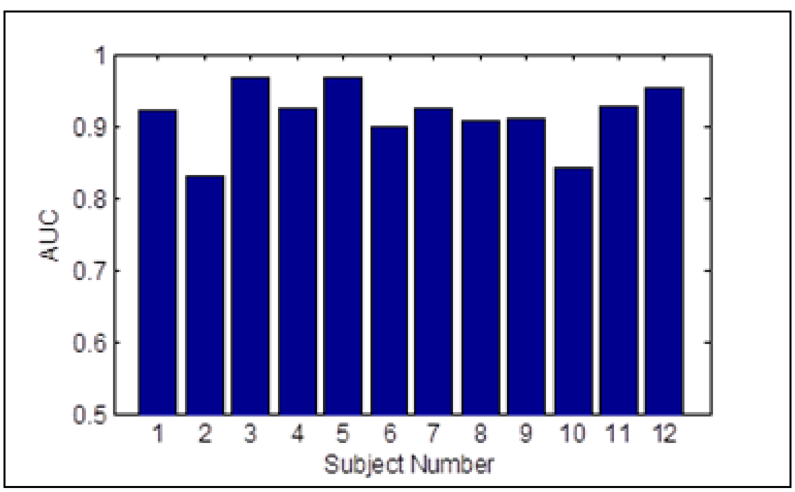

Figure 34. Bar chart showing the area under the ROC curve (AUC) for all subjects in Study 6.

The real-time system uses a threshold of zero for the classifier scores: a score greater than zero indicates a target and less than zero indicates a non-target. A separate analysis can be carried out to compare the classifier results with the behavioral results by adjusting this threshold. For each subject, suppose we set the classifier threshold to the largest number t such that the probability of detection for the threshold t is equal to the subject's behavioral probability of detection. Figure 35a shows a histogram of this behavioral-matched threshold for the subjects in Study 6. Using this threshold, we can then calculate the corresponding false alarm rate and compare it to the false alarm rate for behavior. Figure 35b shows that for many subjects, the false alarm rate from the classifier is almost as good as, and, in some cases, even better than the behavioral false alarm rate.

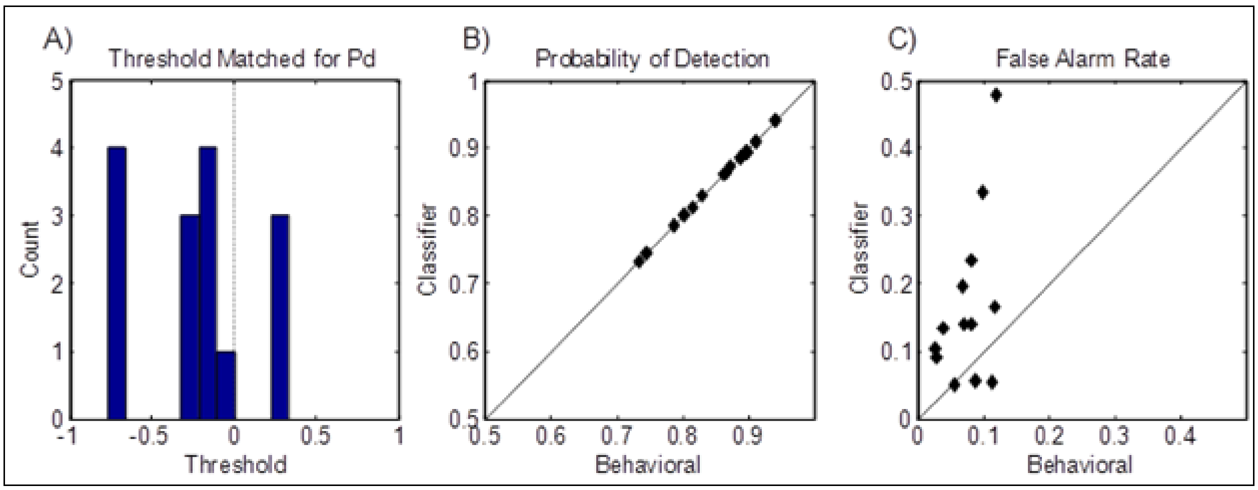

Figure 35. Metrics for classifier performance. Panel c: Histogram of the classifier score thresholds the give the same Pd as behavioral detection for each subject; Panel b: matched Pd for behavioral and classifier performance; Panel c: plot of false alarm rate for behavioral versus classifier with matched Pd.

If the RSVP task is the first step of an image triage process (Sajda et al., 2003; Sajda et al., 2010), we define additional metrics to characterize performance. In this case, the button presses or EEG classifier scores from the RSVP component can be used to sort the video clips for subsequent review by a human operator. For the behavioral-based system, we can re-order the clips so that the clips that elicited a button press are all at the top of the queue. For the RSVP-based system, the clips are re-ordered based upon score, from the highest score to the lowest. The resequencing based on behavioral and RSVP input can be compared with the original ordering by examining the accuracy in the following sense. In figure 36, the re-sequencing of an entire session for two subjects is presented. Here, the fraction of targets is plotted as a function of sequence index for the 2800 video clips. The resequencing via button press or classifier score is bounded on the lower end by the original sequence, where targets and non-targets are presented randomly, and the on the upper end by optimal resequencing, where all targets are presented before the non-targets. For the two subjects shown in figure 36, the button press initially outperforms the classifier, that is, more targets appear at the front of the sequence. After a certain percentage of the targets appear, the classifier results begin to outperform the button press. For the last 10–25% of the targets (for these two subjects), more appear at the front of the classifier-ordered sequence.

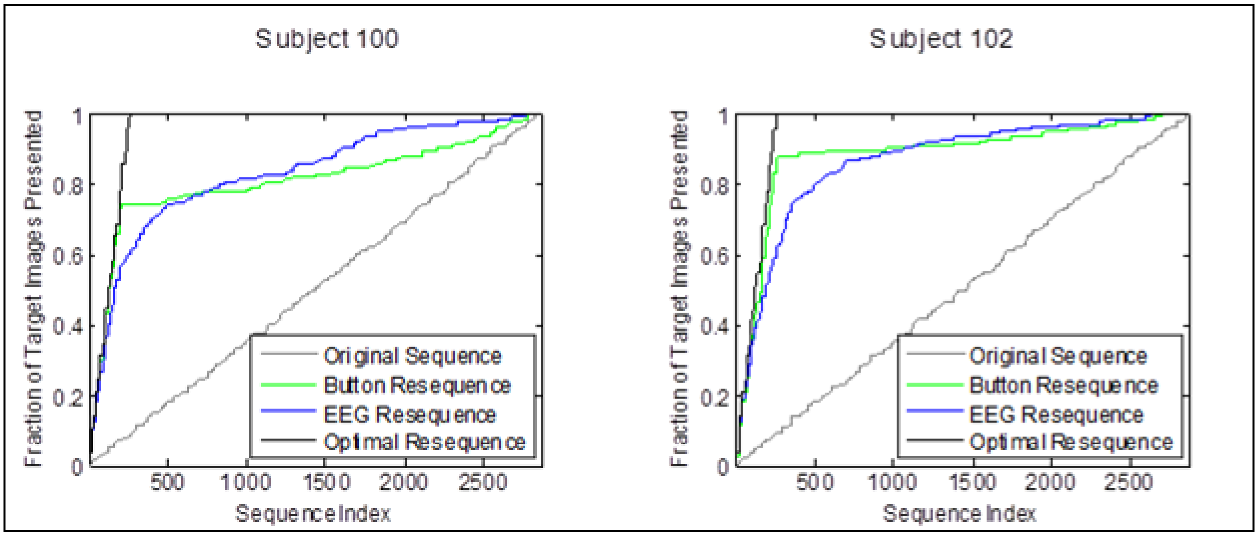

Figure 36. Re-sequencing accuracy. Fraction of target images presented as a function of sequence index. Lower bound: original sequence where targets where presented randomly. Upper bound: optimal re-sequencing where all targets are presented before any non-targets.

The analysis of resequencing accuracy compares the performance of the classifier to a subject's button presses. Often the RSVP-based triage and review will replace a totally manual process of looking for targets while stepping through a sequence of images. A metric that is useful for comparisons is the number of targets detected per unit time. If the goal of the process is to find targets quickly, the best system is the one that results in finding the most targets soonest. Figure 37 illustrates a useful method for comparing performance. For the baseline condition, the subjects manually review all video clips looking for targets. We assume they view the clips for 500 ms each and have an average response time of 750 ms. Assuming the targets are evenly distributed through the original sequence, the targets per time graph for the baseline is a straight line. With RSVP-based triage, first the subject performs RSVP; the images are re-sequenced based upon the classifier score, and the subject reviews the results. In figure 37, the dashed vertical line represents the end of the RSVP period and the red line shows the targets found plotted against time. The area between the red curve and the baseline (positive if the red line is above the baseline graph) quantifies the benefit of triage. In this case, the benefit is modest. If we assume a presentation rate of 100 ms/image clip, the results are more substantial (figure 37b). This metric can help define the parameters for RSVP and inform how an RSVP component might be utilized in the crew-station.

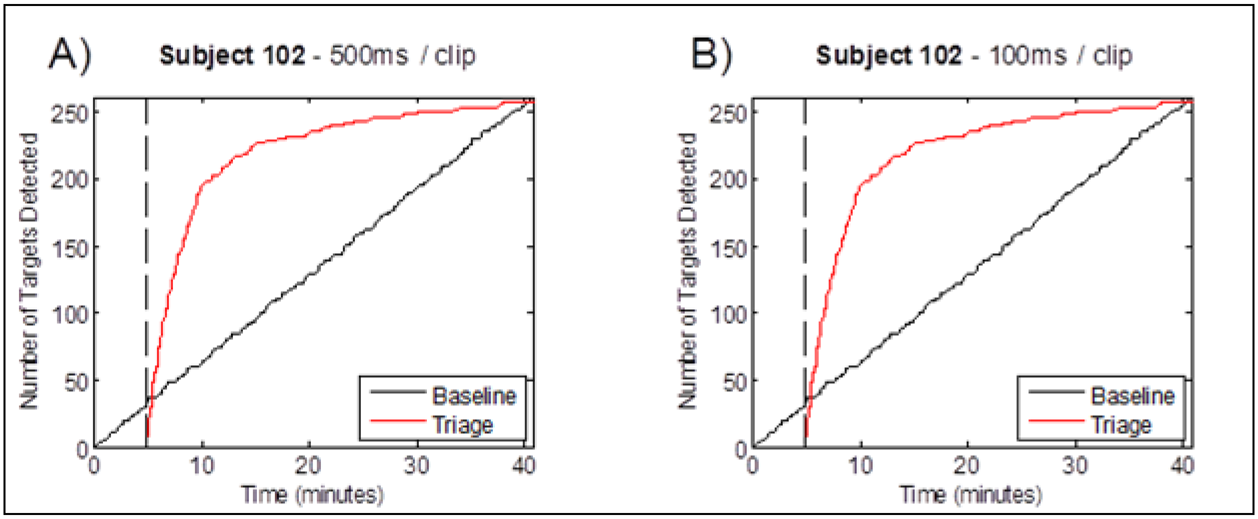

Figure 37. Image triage performance. Number of targets detected as a function of time for baseline and triage (RSVP-sorted) condition. Dashed line indicates end of RSVP component and beginning of manual review. Panel a: Plot shows the performance in the current 500 ms per clip condition; Panel b: plot shows the performance for a hypothetical 100 ms per clip condition (assuming similar classifier performance).

9. Summary of Results

We summarize the key results from Year 1 in table 4.

Table 4. Summary of the results by study number.

Result	Study
When RSVP is presented at fixation, there is no performance impact due to RSVP rate.	1
Performance degrades directly as a function of the distance of the image from fixation.	1
For a given level of performance, targets presented in the periphery must be more salient than targets presented at fixation.	2
Behavioral performance degrades as target frequency increases.	3
Pattern classification performance peaks at 300 ms post-stimulus and is highest when the target frequency is 0.1 or 0.25.	3
If a classifier is trained on data from one target frequency and then applied to data from another target frequency, the performance is degraded. Training with data from a higher target probability condition results in the least degradation.	3
Classifier scores are inversely correlated with target frequency.	4
Target frequency can be estimated from the distribution of scores and used to compensate for changes in this parameter.	4
Behavioral performance is similar under single and dual task conditions.	5
Pattern classification performance for the visual task peaks at 300 ms post-stimulus and is unaffected by the second task.	5
Classifier performs poorly (at chance) on visual stimuli that are shown while the subject is carrying out the auditory task only.	5
There is no significant difference in behavioral performance for the visual task alone compared with the visual and auditory tasks together.	6
There is no significant difference in classifier performance for the visual task alone compared with the visual and auditory tasks together (for the subjects with high classifier performance).	6
Classifier performance degrades for combined auditory and visual tasks for subjects with poor classifier models.	6
Result	**Study**
For many subjects, separate classifiers could detect visual and auditory targets.	6
The pattern classifier can discriminate between successfully detect targets and those that are missed based on neural activity.	7
Classification performance is higher when all post-stimulus activity is used at once (right panel).	7
Although classifiers using either amplitude or power alone perform above chance, amplitude is better. There is little or no benefit when including both amplitude and power together.	7
Latency in the ERP and the classifier score predict classifier accuracy and can be used to improve system performance.	8
Latency in the ERP mirrors the variably in the behavioral response (RT). This variability is partially a reflection of the attentional state of the individual.	9
SAIC's current real-time system can achieve performance levels nearing those of behavior (the upper-bound in this metric formulation).	10
Improvements can be made through 1) better classifier models, 2) Incorporation of attentional state and temporal dynamics into classification scheme and 3) enhanced EEG artifact detection and mitigation.	10

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List of Symbols, Abbreviations, and Acronyms

AB	Attentional Blink
ACC	accuracy
ARL/HRED	Army Research Laboratory/Human Research and Engineering Directorate
ATO	Army Technology Objective
AUC	Area-Under-the-Curve
BCIT	Brain-computer Interactive Technologies
CT2WS	Cognitive Technology Threat Warning System
DARPA	Defense Advanced Research Projects Agency
EEG	Electroencephalography
ERP	Event-related Potential
fMRI	Functional Magnetic Resonance Imaging
FPR	False Positive Rate
HD-Cog	High-Definition Cognition in Operational Environments
IA	Imagery Analyst
ICB	Institute for Collaborative Biotechnologies
LDA	linear discriminant analysis
MGV	manned ground vehicles
NIA	Neurotechnology for Intelligence Analysts
NTG	non-target
P3	P300
Pd	probability of detection
ROC	Receiver Operating Characteristic
ROI	region of interest
RSVP	Rapid Serial Visual Presentation
RT	Reaction Time, Response Time
SAIC	Science Applications International Corporation
SOA	stimulus onset asynchrony
TARDEC	Tank Automotive Research Development and Engineering Command
TPR	True Positive Rate
TRG	target

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